Seeing Failure In Advance: Pre-Generation Failure Diagnosis for Multi-Modal Retrieval-Augmented-Generation

Anonymous ACL submission

Abstract

Multimodal retrieval-augmented generation (MMRAG) systems can fail even when relevant evidence is retrieved, exposing a gap between retrieval and generation. We formulate MMRAG failure diagnosis as an online single-fire decision problem over prefill hidden states, which is distinct from static probing of model internals or post-hoc self-correction. Across InfoSeek, E-VQA, and VISA, we show that hidden states encode both failure occurrence and failure type, with failure detection reaching around 90% accuracy and recall on InfoSeek and E-VQA. We further introduce a Fire-Then-Type prober that separates failure detection from failure typing, improving typed diagnosis over direct classification. Finally, our method matches the response accuracy of final-layer repair while completing diagnosis 16–24% earlier in the prefill. These results show that MMRAG failures can be diagnosed early enough to support targeted generation-time intervention.

1 Introduction

MMRAG has become a standard paradigm for grounding Multi-Modal Large Language Models (MLLMs) in external knowledge, particularly for knowledge-intensive visual question answering where parametric memory is insufficient or stale (Lewis et al., 2020; Lin and Byrne, 2022; Chen et al., 2022). By augmenting an image-question pair with retrieved textual or visual evidence, MMRAG systems aim to produce factual answers without retraining the underlying MLLMs.

Despite steady progress in retrievers and rerankers (Chen et al., 2022; Hu et al., 2023; Zhang et al., 2025c), a persistent puzzle remains. *Improvements in retrieval quality do not translate proportionally into generation gains.* Even when relevant evidence is successfully retrieved and placed in context, MLLMs frequently fail to leverage it (Liu et al., 2024; Li et al., 2025b; Cuconasu et al., 2024). This retrieval-generation gap has been variously attributed to positional bias toward early context (Liu et al., 2024; Yao et al., 2025), knowledge conflicts between parametric and retrieved evidence (Xu et al., 2024; Zhang et al., 2025b), underutilization of fine-grained details, and sensitivity to noise from irrelevant candidates (Li et al., 2025b; Cuconasu et al., 2024). Yet the failure *mechanism*, and crucially *when* during inference the failure becomes detectable, remains poorly characterized for multimodal settings.

Existing remedies for this gap are largely *reactive*. Self-correction frameworks such as Self-Refine (Madaan et al., 2023), Reflexion (Shinn et al., 2023), and Self-RAG (Asai et al., 2023), together with corrective retrieval methods including CRAG (Yan et al., 2024), OmniSearch (Li et al., 2025a), and DeepMMSearch-R1 (Narayan et al., 2025), share a common architectural assumption. They wait for the model to emit a final answer before evaluating its quality and triggering correction. This post-hoc paradigm incurs the full cost of a discarded forward pass and applies a generic retry regardless of whether the underlying issue is a distracting hard negative, an unparseable evidence chunk, or simply missing evidence. Attention-level interventions such as ALFAR (An et al., 2025) act earlier but are constructed under an oracle assumption of top-1 correct evidence, a condition that rarely holds in deployed retrieval pipelines.

In this work, we ask a different question. ***Does the MLLM internally know when it is about to fail, before any output token is generated?*** As an initial motivation, Figure 2 compares hidden states produced under two controlled conditions, *oracle*, where only gold evidence is provided, and *mixed*, where gold evidence is combined with hard negatives. Across three MLLMs, successful cases remain highly similar between the two conditions, whereas other failures show a clear representational divergence at deeper layers. These patterns indicate that MMRAG failures are not only visible in final answers, but are already reflected in the model's internal computation. Drawing on recent text-domain findings that LLM hidden representations cluster systematically by retrieval condition (Yeh and Li, 2026) and that lightweight probes can predict rea-

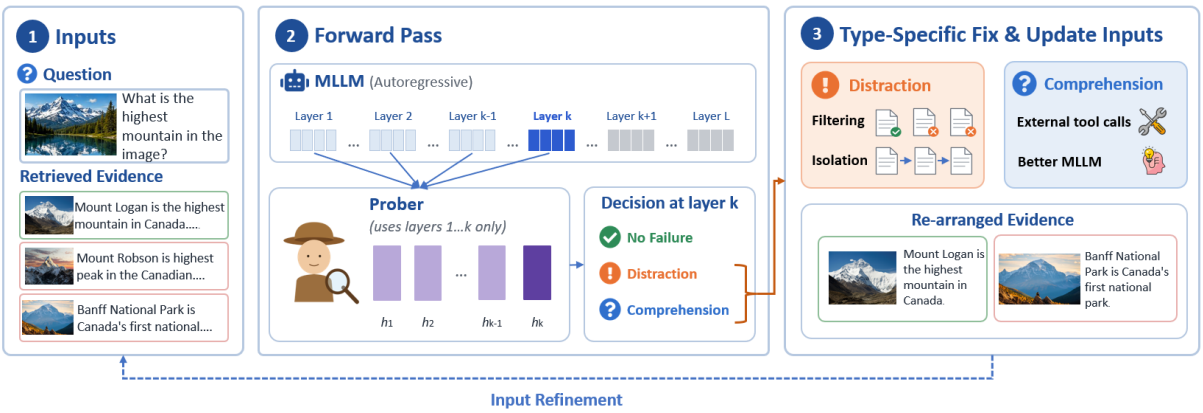

Figure 1: Overview of the proposed early failure routing framework for MMRAG. Given an image-question pair and retrieved evidence, the MLLM performs a forward pass while a lightweight prober monitors hidden-state prefixes at intermediate layers. When the prober fires a failure, it routes the example to a type-specific intervention and refines inputs.

soning correctness mid-trajectory (Zhang et al., 2025a), we analyze the hidden states of contemporary MLLMs under controlled retrieval conditions and find that a usable failure signal emerges at intermediate layers, well before generation completes.

Building on this observation, we propose a lightweight framework, shown in Figure 1, that monitors pre-generation hidden states during the MLLM forward pass, predicts the likely failure mode of the retrieved-context execution, and dispatches a targeted intervention rather than a generic retry. By acting before generation completes, the framework avoids the cost of a discarded forward pass and matches each remedy to the actual cause of failure, whether the retrieved set contains distractors, lacks the needed evidence, or simply exceeds the model's capacity to extract it.

This work raises four research questions. We first ask whether a lightweight prober on MLLMs' hidden states can detect failures before generation completes. We then examine whether early failure routing improves end-to-end MMRAG accuracy over uniform retry. Next, we investigate at which pre-generation transformer depths failure signals emerge, and how the earliness-accuracy trade-off affects routing decisions. Finally, we examine how consistently failure signals appear across different MLLM architectures.

Contributions. Our contributions are threefold.

1. A novel formulation of MMRAG failure diagnosis as an online single-fire early-exit problem, distinct from static hidden-state probing and from post-hoc self-correction. A comparison of our work with others is shown in Table 4 in Appendix.

2. A probing-based early failure routing framework that first distinguishes failure types and dispatches type-specific interventions, in contrast to the uniform-retry assumption of prior self-correction work.

3. An empirical study of where and how reliably failure signals emerge across layers and MLLM architectures.

2 Related Works

We summarize how our framework relates to the closest lines of research in Table 4 in Appendix.

Multimodal retrieval-augmented generation. Retrieval is especially important for knowledge-intensive visual question answering, where answers often require external knowledge beyond the image. Knowledge-based VQA benchmarks and models study how systems retrieve and use textual or structured knowledge for visual questions (Wang et al., 2018; Marino et al., 2019; Gui et al., 2022; Yang et al., 2022). More recent multimodal RAG methods retrieve outside knowledge for VQA (Lin and Byrne, 2022), improve fine-grained cross-modal retrieval (Lin et al., 2023), or retrieve from multimodal image-text memories (Chen et al., 2022; Hu et al., 2023). Dynamic MMRAG systems further incorporate multi-hop retrieval planning and web search tools (Li et al., 2025a; Long et al., 2025; Narayan et al., 2025). Unlike these works, which primarily improve retrieval or retrieval planning, we diagnose whether the MLLM will successfully use the retrieved evidence after it has already been placed in context.

Corrective and self-reflective generation. Several methods improve generation through inference-time feedback or correction. Self-Refine iteratively

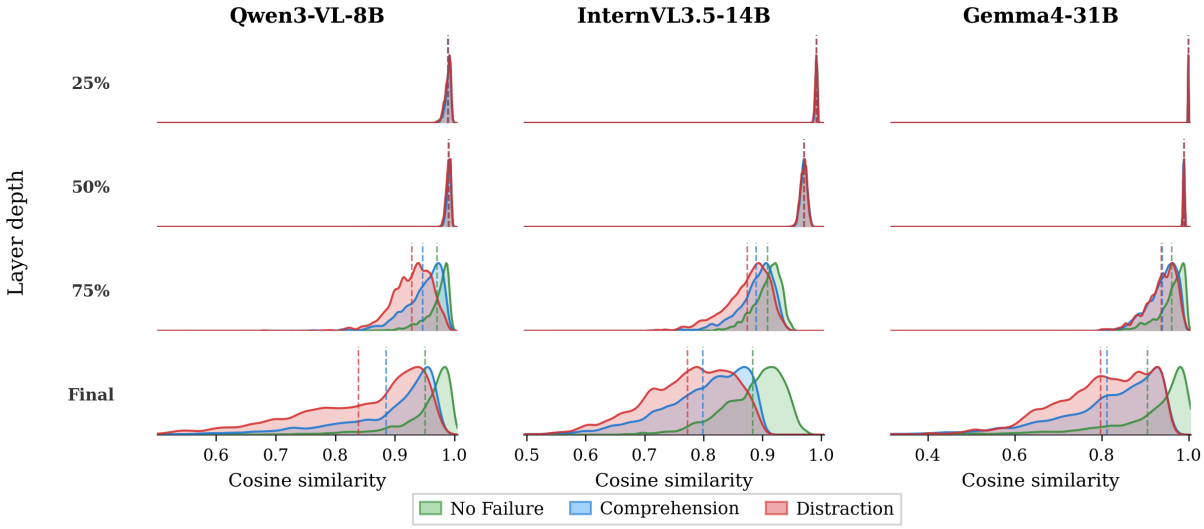

Figure 2: Distribution of cosine similarity between hidden states produced under two retrieval conditions, oracle (gold evidence only) and mixed (gold + hard-negative evidence), across layer depth for three MLLMs on InfoSeek training set. Samples are grouped into three types based on model response correctness. **No Failure**: the model answers correctly under both oracle and mixed conditions. **Comprehension**: the model fails under both conditions, indicating an inability to answer regardless of retrieval quality. **Distraction**: the model succeeds with oracle retrieval but fails when hard-negatives are introduced. Dashed lines indicate group means.

critiques and revises an initial answer (Madaan et al., 2023), Reflexion uses verbal feedback from past failures (Shinn et al., 2023), Self-RAG trains models to retrieve and critique with reflection tokens (Asai et al., 2024), and CRAG estimates retrieval quality to trigger corrective retrieval (Yan et al., 2024). In multimodal settings, OmniSearch and DeepMMSearch-R1 use adaptive planning or tool-based search to improve complex visual question answering (Li et al., 2025a; Narayan et al., 2025). These approaches are largely driven by retrieval-quality estimates, generated critiques, or post-hoc retry. In contrast, we detect impending failure from hidden states before answer generation completes and route the example to a type-specific intervention.

Knowledge utilization and hidden-state probing. Even with relevant evidence, MLLMs may fail due to weak evidence utilization, attention bias, or conflicts between parametric and retrieved knowledge. ALFAR addresses this issue by reallocating attention toward relevant context tokens and adaptively fusing parametric and contextual knowledge (An et al., 2025). More broadly, probing studies show that intermediate representations encode useful information about model behavior (Alain and Bengio, 2017; Belinkov, 2022), including uncertainty, latent knowledge, truthfulness, and reasoning correctness (Kadavath et al., 2022; Burns et al., 2023; Azaria and Mitchell, 2023; Zhang et al., 2025a). In the text-based RAG setting, Yeh and Li (2026) show that retrieved context systematically shapes LLM hidden representations. Our work extends this perspective to MMRAG by probing MLLM hidden states to predict both whether an execution will fail and what type of failure it reflects.

3 Analysis

3.1 Experiment Setup

We train the diagnostic prober using the training splits of InfoSeek (Chen et al., 2023), E-VQA (Mensink et al., 2023) and VISA-paper (Ma et al., 2025). For each example, we run three MLLMs, which are Qwen3-VL-8B (Bai et al., 2025), InternVL3.5-14B (Wang et al., 2025) and Gemma4-31B (Team, 2026), under two retrieved-context conditions. The first is oracle condition, where the model is given the target evidence document. The second is a mixed condition, where the relevant evidence is presented together with retrieved distractor documents. For both conditions, we record the model's pre-generation hidden states at every transformer layer.

For failure detection, each execution is labeled by whether the MLLM answer under that execution is correct (Sec. 3.3). For failure typing, mixed executions are further labeled using the oracle result. A failure is labeled as *Comprehension* if the model is wrong under both conditions, and as *Distraction* if the model is correct under oracle condition but wrong under the mixed condition. More experimental details are shown in Appendix B.

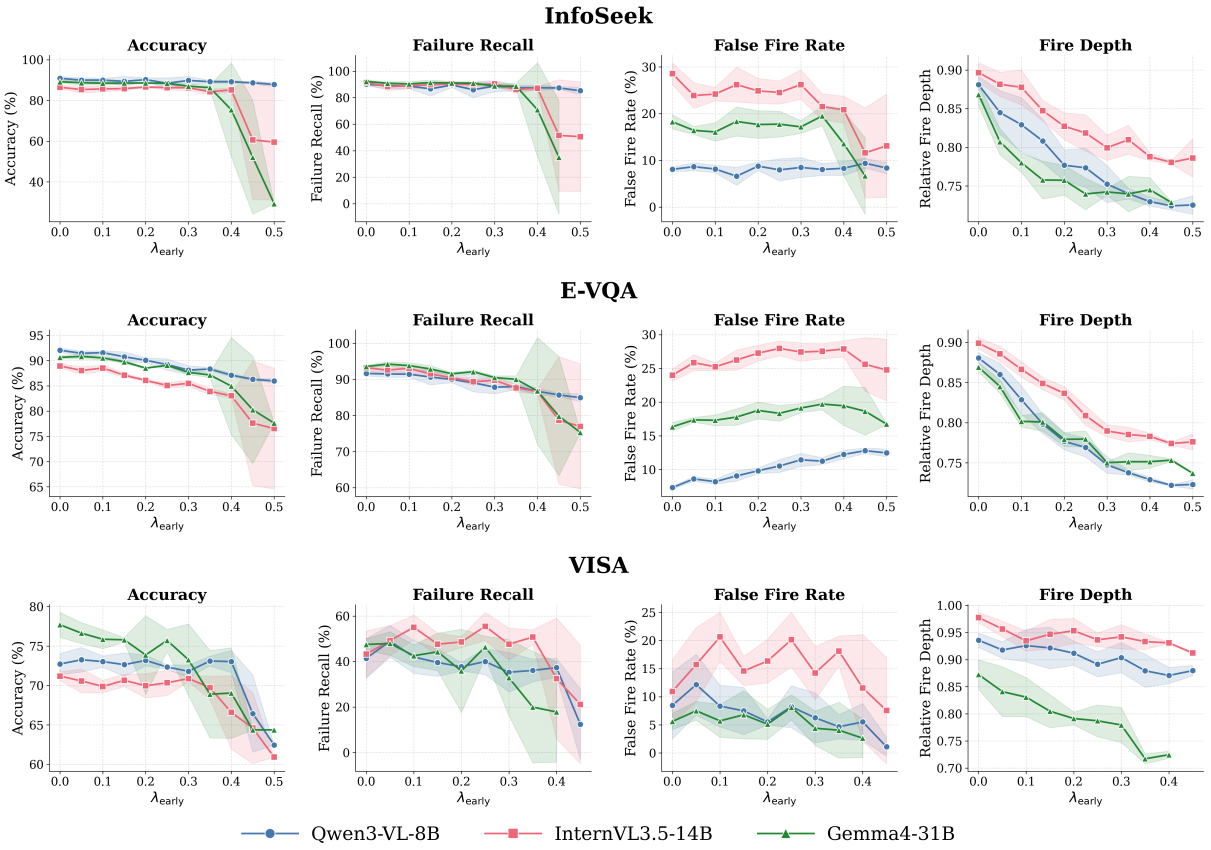

Figure 3: **Failure detection from hidden-state prefixes on three datasets.** We vary the earliness weight λ_{early} to study when failure signals become detectable and how early firing affects detection quality. Higher λ_{early} penalizes late firing more strongly, encouraging the prober to fire earlier when a reliable failure signal is present. Raw values are present in Table 5, 6, 7 in Appendix.

Role of oracle evidence. The oracle condition is used only to construct diagnostic labels under controlled retrieval conditions. It is not provided to the prober at inference time. At test time, the prober observes only the hidden states induced by the retrieved mixed context and does not know which is the oracle.

3.2 When does the failure start to emerge and become detectable?

Our first question is whether MMRAG failures can be detected from the model's internal states before answer generation is completed. We formulate failure detection as an online single-fire decision problem over hidden states, inspired by early-exit and adaptive-computation methods that make intermediate-layer decisions when sufficient evidence is available (Graves, 2016; Teerapittayanon et al., 2016). Given a retrieved-context input, the MLLM processes the prompt through its transformer layers before decoding an answer. At layer k, the prober observes the hidden-state prefix

$$H_{1:k} = [h_1, h_2, \ldots, h_k],$$

where h_k denotes the hidden state at layer k for the current retrieved-context execution. The prober then decides whether to continue processing or to fire a failure signal. Once the prober fires, the decision is final. At each layer k, the prober outputs a conditional firing probability

$$q_k = P(\text{fire at layer } k \mid \text{no earlier fire}, H_{1:k}).$$

This quantity is local to layer k. It represents the probability of firing at the current layer, conditioned on the fact that the prober has not fired at any previous layer. Since the prober is constrained to fire at most once, the probability that it fires for the first time exactly at layer k must also account for not firing at all earlier layers. We denote this first-fire probability by p_k:

$$p_k = q_k \prod_{j<k} (1 - q_j).$$

Thus, q_k is the prober's conditional decision probability at layer k, whereas p_k is the induced probability that the first and only firing event occurs at layer k. For a model with L layers, the probability

of never firing is

$$P_{\text{never fire}} = \prod_{k=1}^{L}(1 - q_k),$$

and the probability of firing at least once is

$$P_{\text{fire}} = 1 - P_{\text{never fire}} = \sum_{k=1}^{L} p_k.$$

In our experiments, we instantiate retrieved-context executions under two retrieval conditions: an oracle-only context, which contains only gold evidence, and a mixed context, which contains both gold evidence and hard-negative evidence. Both settings are treated as retrieved-context executions, allowing us to examine whether failure signals emerge under clean evidence as well as in the presence of distractors.

Given a binary label $y \in \{0, 1\}$, where $y = 1$ denotes failure, i.e., the final model answer is incorrect, and $y = 0$ denotes no failure, i.e., the final model answer is correct, we train the prober with the sequence-level binary negative log-likelihood

$$\mathcal{L}_{\text{seq}} = -y \log P_{\text{fire}} - (1 - y) \log P_{\text{never fire}}.$$

This objective directly matches the online single-fire evaluation setting. Failure examples are rewarded if the prober fires at least once, while no-failure examples are rewarded only if the prober never fires.

However, correctness alone is not sufficient. A prober that waits until the final layer may be accurate, but it leaves little room for downstream intervention. Conversely, a prober that fires too aggressively in early layers may interrupt executions that would have eventually produced correct answers. Therefore, the prober should fire only when the failure signal is reliable, while still firing early enough to be useful.

To encourage timely decisions, we introduce an earliness cost on failure examples. Conditioned on the prober firing, the expected relative firing depth is

$$d_{\text{fire}} = \frac{1}{P_{\text{fire}}} \sum_{k=1}^{L} \frac{k}{L} p_k.$$

The final objective is

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{seq}} + \lambda_{\text{early}} y d_{\text{fire}}.$$

Here, λ_{early} controls how strongly late firing is penalized. When $\lambda_{\text{early}} = 0$, the prober optimizes only the sequence-level single-fire objective. Increasing λ_{early} encourages the prober to fire earlier on failure examples, but only when the hidden states provide sufficient evidence to preserve the sequence-level objective.

Figure 3 reports the earliness behavior of the proposed prober on the InfoSeek test set across three open-sourced MLLMs. We vary λ_{early}, which controls the cost of late firing, and examine how the prober trades off overall accuracy, failure recall, false-fire rate, and firing depth. As λ_{early} increases, the prober is able to fire at earlier layers while maintain the same accuracy. This demonstrates the failure signal already becomes reliable at intermediate depths.

Table 1 shows that the accuracy drop at large λ_{early} is largely driven by reduced fire rates. Rather than firing earlier, the prober often becomes overly conservative and chooses not to fire, which lowers false fires but also misses true failures. This collapse is most evident for Gemma 4 on InfoSeek and all three models on VISA at $\lambda_{\text{early}} = 0.5$. Thus, moderate earliness weights encourage useful earlier intervention, whereas overly large weights reduce failure coverage.

The failure signal is also weaker on VISA than on InfoSeek and E-VQA. We attribute this to VISA-paper's screenshot-based scientific evidence, which is more visual and layout-dependent than Wikipedia-derived textual evidence. Together with the filtered three-candidate setting, this may make the oracle–mixed contrast less separable in hidden-state space and reduce detection reliability.

Key Takeaway

Failure signals emerge during the prefill stage, often before the final transformer layers. This enables the prober to intervene before answer decoding, rather than post-hoc correction after a completed answer.

3.3 Does the model internally encode the type of failure?

Our second question is whether the hidden states encode not only whether an execution will fail, but also why it will fail. This distinction is important because different failure mechanisms call for different interventions. A failure caused by distracting hard-negative evidence should be handled by evidence filtering or reranking, whereas a failure that persists even with oracle evidence is unlikely to be fixed by simply removing distractors.

We extend the prober with a type prediction head in addition to the fire head described in Section 3.2. The fire head decides when to interrupt the current execution, while the type head predicts the reason for failure once the fire head fires. Thus, the type

Dataset	Model	λ_{early}										
		0	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
InfoSeek	Qwen	$57.5_{\pm 1.7}$	$56.8_{\pm 1.9}$	$56.2_{\pm 1.6}$	$54.4_{\pm 4.4}$	$56.9_{\pm 1.6}$	$54.7_{\pm 5.1}$	$56.1_{\pm 3.5}$	$55.9_{\pm 2.8}$	$55.5_{\pm 1.9}$	$55.9_{\pm 1.2}$	$54.4_{\pm 2.6}$
	InternVL	$75.9_{\pm 1.6}$	$72.4_{\pm 3.2}$	$72.9_{\pm 2.3}$	$74.1_{\pm 2.8}$	$74.2_{\pm 1.3}$	$73.7_{\pm 2.0}$	$74.5_{\pm 1.8}$	$70.2_{\pm 2.9}$	$70.8_{\pm 1.5}$	$41.7_{\pm 38.1}$	$41.3_{\pm 37.8}$
	Gemma	$70.6_{\pm 1.1}$	$69.1_{\pm 0.8}$	$68.4_{\pm 2.5}$	$70.0_{\pm 2.4}$	$69.6_{\pm 1.9}$	$69.5_{\pm 1.6}$	$67.8_{\pm 1.0}$	$68.4_{\pm 2.6}$	$54.1_{\pm 30.2}$	$26.7_{\pm 36.6}$	0.0
E-VQA	Qwen	$57.9_{\pm 1.4}$	$58.1_{\pm 0.8}$	$57.3_{\pm 1.0}$	$58.3_{\pm 2.1}$	$57.4_{\pm 0.9}$	$57.5_{\pm 2.2}$	$56.8_{\pm 1.4}$	$57.6_{\pm 1.6}$	$56.6_{\pm 0.8}$	$56.2_{\pm 0.6}$	$56.2_{\pm 1.8}$
	InternVL	$76.1_{\pm 0.7}$	$76.1_{\pm 1.4}$	$76.3_{\pm 1.0}$	$75.4_{\pm 1.2}$	$74.8_{\pm 0.6}$	$74.2_{\pm 1.1}$	$74.3_{\pm 0.8}$	$72.8_{\pm 1.2}$	$72.1_{\pm 0.7}$	$65.6_{\pm 16.0}$	$64.1_{\pm 15.8}$
	Gemma	$70.9_{\pm 0.4}$	$71.7_{\pm 0.4}$	$71.2_{\pm 1.3}$	$70.9_{\pm 1.1}$	$70.2_{\pm 0.7}$	$70.5_{\pm 0.7}$	$69.6_{\pm 0.4}$	$69.4_{\pm 1.1}$	$67.1_{\pm 12.6}$	$61.9_{\pm 14.2}$	$58.1_{\pm 0.1}$
VISA	Qwen	$20.8_{\pm 7.7}$	$26.0_{\pm 6.5}$	$21.0_{\pm 5.6}$	$19.5_{\pm 5.2}$	$17.6_{\pm 0.9}$	$20.2_{\pm 5.0}$	$17.2_{\pm 6.7}$	$16.5_{\pm 3.6}$	$17.5_{\pm 3.7}$	$5.4_{\pm 7.5}$	0.0
	InternVL	$23.6_{\pm 8.3}$	$28.8_{\pm 7.4}$	$34.1_{\pm 5.3}$	$27.5_{\pm 3.8}$	$29.0_{\pm 3.6}$	$33.9_{\pm 5.8}$	$27.3_{\pm 6.3}$	$30.9_{\pm 2.8}$	$19.8_{\pm 18.1}$	$12.9_{\pm 17.8}$	0.0
	Gemma	$20.5_{\pm 1.0}$	$21.9_{\pm 3.0}$	$18.9_{\pm 3.8}$	$20.2_{\pm 6.3}$	$16.1_{\pm 9.1}$	$21.8_{\pm 3.1}$	$14.6_{\pm 8.5}$	$9.7_{\pm 13.3}$	$8.0_{\pm 11.2}$	0.0	0.0

Table 1: Overall fire rate (%) on InfoSeek, E-VQA and VISA test set across earliness weights λ_{early}. Each cell is $\text{mean}_{\pm\text{std}}$ across five seeds.

head is conditioned on the fire head. We assign type labels by comparing the model's behavior under paired oracle and mixed retrieval conditions. Let $r_o, r_m \in \{0, 1\}$ denote answer correctness under oracle-only and mixed evidence, respectively. We define three labels:

$$(r_o, r_m) = (1, 1) \Rightarrow \text{No Failure},$$

$$(r_o, r_m) = (0, 0) \Rightarrow \text{Comprehension},$$

$$(r_o, r_m) = (1, 0) \Rightarrow \text{Distraction}.$$

The No Failure label corresponds to executions that remain correct even in the presence of hard negatives. The Comprehension label captures examples where the model fails even with gold evidence, suggesting an inability to understand, ground, or use the relevant information. The Distraction label isolates cases where hard negatives change an otherwise correct oracle execution into an incorrect mixed-context execution. This distinction mirrors common RAG failure decompositions between generation-side limitations, context conflict, and noise from irrelevant or misleading retrieved documents (Liu et al., 2024; Cuconasu et al., 2024; An et al., 2025).

Since the type head is used only after the fire head fires, we train it under the induced first-fire distribution. For an example with type label c, $c \in \{\text{Comprehesion}, \text{Distraction}\}$, the type prediction conditioned on firing is

$$P(c \mid \text{fire}) = \frac{1}{P_{\text{fire}}} \sum_{k=1}^{L} p_k \, P(c \mid H_{1:k}).$$

The corresponding type loss is

$$\mathcal{L}_{\text{type}} = -I[c \neq \text{No Failure}] \log P(c \mid \text{fire}).$$

We apply this loss only to actionable failure types, since No Failure examples should be handled by the fire head not firing rather than by assigning a type after firing.

The final training objective adds type loss to the single-fire objective is

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{seq}} + \lambda_{\text{early}} y d_{\text{fire}} + \mathcal{L}_{\text{type}}.$$

This formulation ensures that the prober first learns whether and when to fire, and the type head learns to classify the failure mode at the layers where firing is likely.

We compare the proposed Fire-Then-Type (FTT) prober against a Direct 3-Class (D3C) baseline. FTT is the fire-conditioned model described above. The fire head first determines whether and when to interrupt the execution, and the type head predicts the failure mode under the induced first-fire distribution. D3C removes this decomposition and directly predicts No Failure, Comprehension, or Distraction from the hidden-state prefix.

Figure 4 compares the two methods across λ_{early} on three metrics. Full per-lambda results are reported in Table 8, 9, 10 in Appendix. Our FTT improves overall accuracy over D3C across the all the MLLMs. The advantage is clearest for Qwen3-VL and InternVL, where FTT also substantially improves Distraction recall while preserving high Comprehension recall. This supports that separating failure detection from failure typing makes the diagnostic signal easier to extract from hidden states.

Gemma shows a more mixed pattern. FTT improves overall accuracy and Comprehension recall, but does not improve Distraction recall over D3C. Thus, the fire-then-type decomposition is beneficial for typed diagnosis overall, but its benefit for identifying distraction failures is model-dependent.

Key Takeaway

Hidden states in prefill stage encode not only whether an execution will fail, but also the likely failure mode.

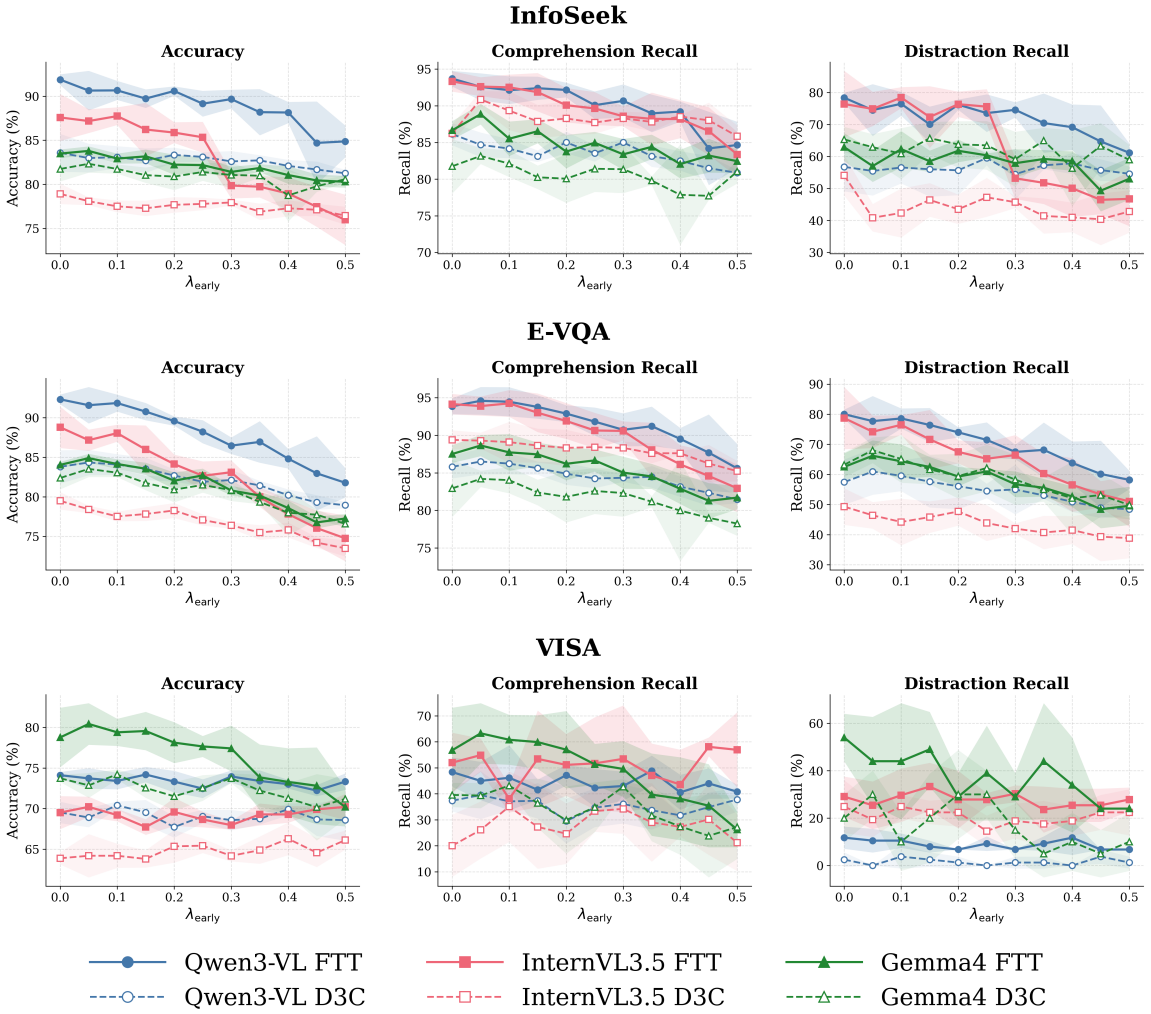

Figure 4: **Failure type prediction from hidden-state prefixes.** We compare the proposed Fire-Then-Type (FTT) prober with a direct 3-class (D3C) baseline across different earliness weights. FTT more reliably separates failure detection from failure typing, yielding stronger overall diagnosis and improved recall for actionable failure modes. Raw values are present in Table 8, 9, 10.

3.4 Does DISTRACTION failure intervention improve answer generation?

Our final question asks whether typed failure diagnosis can support downstream repair. We focus on DISTRACTION failures, where the model answers correctly with oracle evidence but fails after distractors are added. In this case, the model has the necessary capability, and the failure is induced by interfering retrieved context. By contrast, COMPREHENSION failures persist even with oracle evidence, suggesting that context removal alone is unlikely to address the underlying error. We therefore study context-level repair for DISTRACTION and leave COMPREHENSION repair to future work.

Our repair policy uses hidden states from the prober's firing layer, i.e., the layer at which the prober commits to a DISTRACTION prediction. This keeps the intervention online-causal. The evidence to remove is selected using only representations available at the time of diagnosis. For each retrieved evidence item, we pool hidden states over its tokens and compare this representation with the final-token representation at the same layer to obtain a model-focus score. We then remove the document with the largest mismatch between model focus and retrieval relevance, corresponding to evidence that receives disproportionately high internal focus relative to its retriever score.

We compare against four controls. ALWAYS APPLY removes the highest-mismatch document for every example using final-layer hidden states, testing the strength of the mismatch signal without online routing. RANDOM REMOVAL and LOW RELEVANCE use the same prober-triggered routing as our method but remove a random document or the lowest-relevance document, respectively. ORACLE (UB) provides only the gold evidence and serves as an upper bound for distraction repair.

Dataset	Model	No fix	Always	Random	Low Rel.	Oracle (UB)	OURS	Avg. layer when failure detected	Prefill saved
InfoSeek	Qwen3-VL-8B	38.1	42.5	39.2	39.7	**43.8**	42.7	28.7 / 37	22.4%
	InternVL3.5-14B	21.6	25.4	22.5	22.1	**27.3**	25.3	33.9 / 41	17.3%
	Gemma4-31B	28.4	29.7	29.2	29.7	**30.9**	30.1	46.2 / 61	24.3%
E-VQA	Qwen3-VL-8B	54.9	65.7	54.1	58.6	**69.8**	66.1	28.7 / 37	22.4%
	InternVL3.5-14B	28.7	36.2	28.7	31.0	**51.4**	36.0	34.3 / 41	16.3%
	Gemma4-31B	45.2	51.4	46.2	47.9	**54.2**	51.5	47.5 / 61	22.1%
VISA	Qwen3-VL-8B	63.8	64.1	62.0	64.1	**65.9**	64.7	33.7 / 37	8.9%
	InternVL3.5-14B	45.0	50.6	46.4	49.8	**55.2**	51.1	39.1 / 41	4.6%
	Gemma4-31B	61.7	62.8	60.9	62.1	**66.1**	63.2	48.3 / 61	20.8%

Table 2: **Prober-triggered context repair results on the three datasets.** ALWAYS applies the removal policy to all samples, while RANDOM and LOW REL. use the prober-triggered routing but differ in how the removed document is selected. ORACLE (UB) evaluates the answer accuracy when only the gold evidence is provided, and therefore represents the upper bound for distractor-removal repair. All numbers are percentage. The second-to-last column reports the average layer index at which the prober fires, averaged over five seeds at $\lambda_{\text{early}} = 0.2$, out of the model's total layer count. The rightmost column reports the remaining prefill depth before the final layer. The best result in each row is shown in bold, and the second-best result is underlined.

Table 2 reports answer accuracy under each dataset's evaluation protocol with $\lambda_{\text{early}} = 0.2$. OURS consistently improves over the original retrieved context, showing that diagnosed DISTRACTION failures can be repaired by suppressing harmful evidence. The gains are not explained by removing arbitrary or low-ranked documents: both RANDOM REMOVAL and LOW RELEVANCE yield smaller improvements, indicating that the hidden-state mismatch captures interference beyond retriever relevance alone.

The comparison with ALWAYS APPLY clarifies the role of routing. Although ALWAYS APPLY sometimes achieves slightly higher aggregate accuracy, it is a final-layer control. That is, it requires the full prefill computation and intervenes on every example. In contrast, OURS uses representations from the prober's firing layer and applies repair only when a DISTRACTION failure is predicted. As shown in Table 2, the prober fires before the final layer across all models, leaving non-trivial remaining prefill depth before final-layer representations are reached. Thus, OURS provides a better online intervention trade-off, recovering most of the benefit of hidden-state-guided repair while avoiding final-layer dependence and unnecessary repair on examples not diagnosed as DISTRACTION.

The earliness benefit varies by dataset. On InfoSeek and E-VQA, OURS achieves accuracy comparable to ALWAYS APPLY while leaving 16–24% of the prefill depth before final-layer representations are reached. On VISA, the remaining prefill depth is smaller for Qwen3-VL-8B and InternVL3.5-14B, and OURS does not always match ALWAYS APPLY in accuracy. This is consistent with the weaker failure signal observed in Section 3.2. When the diagnostic signal is less separable, the prober must fire later to remain reliable. Thus, VISA serves as a harder stress test, suggesting that screenshot-based scientific evidence requires stronger diagnostics.

Finally, the gap between our method and the oracle upper bound shows both the promise and the limitation of context-level repair. Across models, the strategy recovers a substantial portion of the achievable improvement, but it does not fully close the gap to the oracle. This suggests that failure diagnosis can be used not only for post-hoc analysis, but as an actionable signal for improving generation-time behavior.

Key Takeaway

Pre-Generation diagnosis enables selective context repair before final-layer representations are reached, recovering most of the benefit of final-layer repair while avoiding unnecessary intervention.

4 Conclusion

We investigated whether MMRAG failures can be diagnosed before answer generation. By probing MLLM hidden states under controlled retrieval conditions, we show that pre-generation representations encode both failure occurrence and failure type. Our early failure routing framework separates DISTRACTION from COMPREHENSION failures, with routing decisions emerging during the pre-generation forward pass at intermediate-to-late prefill depths. For DISTRACTION failures, prober-guided repair improves answer accuracy by suppressing hard negatives. These findings highlight early internal diagnosis as a promising direction for more reliable and efficient MMRAG systems.

Limitations

This work studies pre-generation failure diagnosis under controlled oracle-mixed retrieval pairs. The oracle condition is used to construct clean diagnostic labels, allowing us to separate failures caused by distracting retrieved evidence from failures that persist even when oracle evidence is provided. However, oracle evidence is not assumed at inference time. The prober makes predictions from the hidden states of the retrieved mixed context alone. This controlled setup is useful for isolating failure mechanisms, but it does not cover all failure modes in deployed MMRAG systems, where oracle evidence may be absent, partially relevant, or ambiguously defined. Our repair module is intended as a proof-of-concept rather than a complete intervention strategy. We focus on DISTRACTION failures and use a simple hidden-state-guided context removal policy to show that early diagnosis can support targeted generation-time repair. Future work can explore stronger interventions, such as adaptive re-retrieval, evidence rewriting, or reasoning support for COMPREHENSION failures. Finally, the diagnostic signal varies across datasets and models, with weaker results on VISA than on InfoSeek and E-VQA. This suggests that diagnosability may depend on dataset structure, evidence granularity, and retrieval-candidate quality.

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A Details of Dataset

We evaluate early failure diagnosis on three knowledge-intensive multimodal QA datasets: InfoSeek, E-VQA, and VISA. Table 3 summarizes the dataset statistics and the retrieval evidence source used in our experiments.

InfoSeek. InfoSeek is a visual information-seeking QA benchmark designed for questions that cannot be answered from the image or common-sense knowledge alone (Chen et al., 2023). The dataset contains about 1.3M image-question-answer triplets over roughly 11K visual entities, with approximately 934K training examples, 73K validation examples, and 348K test examples. Since the public test labels are not available, we evaluate on the validation split. In our MMRAG setup, InfoSeek is paired with a 100K-document Wikipedia knowledge base. For each query, the oracle condition contains the target evidence document, while the mixed condition combines the target evidence with hard negatives retrieved from this knowledge base.

E-VQA. E-VQA, or Encyclopedic-VQA, is a large-scale visual question answering benchmark focused on detailed properties of fine-grained categories and instances (Mensink et al., 2023). It contains 221K unique question-answer pairs, each paired with up to five images, resulting in about 1M image-question-answer triplets. The dataset is supported by a controlled Wikipedia-derived knowledge base with about 2M pages. We use E-VQA as a Wikipedia-grounded MMRAG setting and follow the dataset's prescribed answer evaluation protocol.

VISA-paper. VISA is a retrieval-augmented generation benchmark with visual source attribution, where models must answer a question and identify supporting evidence in retrieved document screenshots (Ma et al., 2025). VISA contains multiple subsets, including Wiki-VISA, based on Wikipedia webpage screenshots, and Paper-VISA, derived from PubLayNet and focused on paper-style scientific documents. Since InfoSeek and E-VQA already cover Wikipedia or encyclopedic evidence, we use the Paper-VISA subset as a complementary non-Wikipedia setting. Paper-VISA contains 100K training examples and 3,000 test examples in the original release. In our experiments, after filtering to examples with three retrieved candidates, we use 71,010 training examples and 2,160 test examples. The mixed condition is constructed from the target evidence screenshot and the provided candidate distractors.

B Experimental Protocol

B.1 Prober Architecture

All probers for binary failure detection, Fire-Then-Type (FTT), and Direct 3-Class (D3C) share a single backbone architecture and differ only in their classification heads and training objective. The input is the hidden state prefix until layer-k, $H_{1:k} = [h_1, h_2, \ldots, h_k]$. $k \leq N$, where N is the depth of the underlying MLLM, namely embedding plus transformer layers ($N = 37$ for Qwen3-VL-8B, $N = 41$ for InternVL3.5-14B, and $N = 61$ for Gemma4-31B). We linearly project to $d_{\text{model}} = 256$, add a learnable per-layer positional embedding, prepend a learnable [CLS] token, and run a 2-layer transformer encoder with $n_{\text{heads}} = 8$, FFN dimension $4 \times d_{\text{model}}$, GELU, and dropout $= 0.3$, followed by LayerNorm.

To realise online prediction, at each candidate fire layer $k \in \{1, \ldots, N\}$ we re-run the encoder with a key-padding mask that zeroes out positions larger than k, read the [CLS] state, and apply the relevant classification head.

The fire head (used in RQ1 and FTT) is an MLP mapping from $d \to 128 \to 1$, producing $q_k =$

Dataset	Evidence source	KB / candidates	Train	Test / Eval
InfoSeek	Wikipedia	100K docs	934K	73K val
E-VQA	Wikipedia	2M pages	221K	5.7K test
VISA-paper	Paper screenshots	-	71K usable / 100K total	2.16K test usable / 3K total

Table 3: Dataset statistics used in our experiments. For InfoSeek, we evaluate on the validation split because the public test answers are not available. For VISA, we use the Paper-VISA subset rather than Wiki-VISA, since InfoSeek and E-VQA already provide Wikipedia/encyclopedic evidence settings.

$P(\text{fire at } k \mid \neg\text{fired before})$. The type head in FTT is an MLP mapping from $d \to 128 \to 2$ over {COMP, DIST}, read out at the fired layer. The D3C is an MLP mapping from $d \to 128 \to 3$) over {NF, COMP, DIST}, with no separate firing step. For FTT we use the *soft-type* loss, in which the type cross-entropy at layer k is weighted by q_k, making the type head answerable wherever the hazard fires. All three variants add an earliness penalty $\lambda_{\text{early}}\, E[k_{\text{fire}}]/N$ on failure examples, and the sweep over λ_{early} traces the recall-depth Pareto frontier.

B.2 Answer Evaluation in Section 3.4

We apply each dataset's prescribed scorer uniformly across the two execution conditions (Oracle and Mixed). For **InfoSeek** we use the upstream STRING / NUMERICAL / TIME exact-match scorer with the dataset's normalization (Chen et al., 2023). For **E-VQA** we use the upstream encyclopedic-VQA scorer (Mensink et al., 2023), which applies pipe-separated alternative EM for single-answer questions and set-IoU ≥ 0.5 for `multi_answer` questions. A BEM (Bulian et al., 2022) fallback for paraphrase equivalence is wired in but disabled on our hosts, so reported numbers are EM-only. For **VISA** we apply the E-VQA scorer to the `short_answer` field.

B.3 Hard-Negative Construction

For each query, the mixed condition is built by shuffling the oracle evidence with $K-1$ distractors drawn from the source dataset's top-K retrieval candidates. "Hard" here is in the retrieval-similarity sense, not adversarially mined. For **InfoSeek** and **E-VQA**, we use the top-5 candidates from an EVA-CLIP retriever over the Wikipedia knowledge base. For **VISA**, we use the queries that contains three candidates ($K = 3$) shipped with the source release leaving 71,010 out of 100,000 usable samples for training, and 2,160 out of 3,000 samples for testing.

B.4 Hyperparameter Selection

We train each prober for up to 1000 epochs with AdamW with lr $= 1 \times 10^{-4}$, weight decay $= 1 \times 10^{-2}$ and batch size 256. We also apply early stopping on validation accuracy with patience $= 10$. We do not tune λ_{early}. We sweep the entire grid $\lambda_{\text{early}} \in \{0.00, 0.05, \ldots, 0.50\}$ and report mean and standard deviation over 5 random seeds (42–46). Training for each (model, dataset, prober) combination runs on a single NVIDIA A6000 in under 10 hours for Qwen3-VL-8B and InternVL3.5-14B; Gemma4-31B takes ∼20 hours owing to its 61-layer hidden-state input.

C Licenses

We use publicly released datasets, models, and software resources in accordance with their original licenses and intended research use. We do not redistribute third-party datasets, model checkpoints, or external knowledge bases.

Datasets. InfoSeek (Chen et al., 2023) is released under the Apache-2.0 license. E-VQA (Mensink et al., 2023) is released through the Google Research repository, where datasets are released under CC BY 4.0 and source code under Apache-2.0. For VISA (Ma et al., 2025), we use the released Paper-VISA subset following the terms of the original benchmark release. Since the public paper/release page does not clearly specify a separate dataset license, we do not redistribute VISA data and only use it for research evaluation

Models and software. We evaluate publicly released MLLMs, including Qwen3-VL-8B (Bai et al., 2025), InternVL3.5-14B (Wang et al., 2025), and Gemma4-31B (Team, 2026), under Apache-2.0. Our implementation builds on standard open-source libraries, including PyTorch and Hugging Face Transformers, under their corresponding licenses.

Method	Multi-modal	RAG-specific	Online sequential decision	Typed failure diagnosis	Drives inter-vention	Pre-generation
Static hidden-state probing						
Kadavath et al. (2022)	✗	✗	✗	✗	✗	—
Burns et al. (2023)	✗	✗	✗	✗	✗	—
Azaria and Mitchell (2023)	✗	✗	✗	✗	✗	—
Zhang et al. (2025a)	✗	✗	✗	✗	✗	✗
Yeh and Li (2026)	✗	✓	✗	✗	✗	—
Self-correction / corrective retrieval						
Self-Refine (Madaan et al., 2023)	✗	✗	✗	✗	✓	✗
Reflexion (Shinn et al., 2023)	✗	✗	✗	✗	✓	✗
Self-RAG (Asai et al., 2024)	✗	✓	✗	✗	✓	✗
CRAG (Yan et al., 2024)	✗	✓	✗	✗	✓	✗
OmniSearch (Li et al., 2025a)	✓	✓	✗	✗	✓	✗
DeepMMSearch-R1 (Narayan et al., 2025)	✓	✓	✗	✗	✓	✗
Attention-level intervention						
ALFAR (An et al., 2025)	✓	✓	✗	✗	✓	✓
Ours	✓	✓	✓	✓	✓	✓

Table 4: Positioning of our framework relative to closely related lines of work. **Multimodal**: handles image-question inputs, not text-only. **RAG-specific**: targets failures induced by retrieved context, rather than general model behavior. **Online sequential decision**: makes a per-layer fire/no-fire decision during prefill with an earliness cost, rather than reading a single fixed representation or waiting for full generation. **Typed failure diagnosis**: distinguishes failure modes (e.g., DISTRACTION vs. COMPREHENSION) rather than producing a single correct/incorrect signal. **Drives intervention**: the diagnostic signal is used to modify inputs or generation, not only for analysis. **Pre-generation**: diagnosis is available before any output token is decoded. A dash (—) indicates the dimension is not applicable to that work's setting.

Model	λ_{early}	Accuracy (%)	Failure Recall (%)	False Fire Rate (%)	Fire Depth
Qwen3-VL-8B	0.00	90.85 ± 0.99	90.13 ± 1.40	8.08 ± 0.50	0.881 ± 0.011
	0.05	89.99 ± 1.18	89.06 ± 2.29	8.64 ± 0.86	0.845 ± 0.028
	0.10	89.99 ± 0.91	88.72 ± 1.97	8.14 ± 0.80	0.829 ± 0.035
	0.15	89.38 ± 2.42	86.65 ± 5.27	6.60 ± 1.92	0.808 ± 0.028
	0.20	90.20 ± 0.94	89.50 ± 1.95	8.76 ± 0.89	0.777 ± 0.020
	0.25	88.46 ± 2.63	86.05 ± 5.95	7.96 ± 2.36	0.773 ± 0.025
	0.30	89.82 ± 2.00	88.68 ± 4.28	8.48 ± 2.12	0.752 ± 0.024
	0.35	89.21 ± 0.74	87.37 ± 2.05	8.05 ± 1.28	0.740 ± 0.007
	0.40	89.18 ± 0.71	87.47 ± 2.01	8.30 ± 1.51	0.730 ± 0.006
	0.45	88.66 ± 0.42	87.34 ± 1.11	9.38 ± 1.05	0.724 ± 0.005
	0.50	87.83 ± 1.16	85.25 ± 2.70	8.36 ± 1.18	0.725 ± 0.012
InternVL3.5-14B	0.00	86.47 ± 0.88	91.41 ± 1.34	28.57 ± 2.32	0.897 ± 0.013
	0.05	85.35 ± 1.66	88.38 ± 2.99	23.87 ± 2.74	0.881 ± 0.016
	0.10	85.68 ± 1.40	88.92 ± 2.26	24.20 ± 1.45	0.878 ± 0.022
	0.15	85.81 ± 0.92	89.75 ± 2.19	26.22 ± 3.73	0.847 ± 0.013
	0.20	86.60 ± 0.41	90.36 ± 0.70	24.87 ± 2.69	0.827 ± 0.017
	0.25	86.26 ± 0.98	89.81 ± 1.74	24.54 ± 2.46	0.819 ± 0.024
	0.30	86.22 ± 1.42	90.30 ± 1.72	26.22 ± 3.16	0.799 ± 0.016
	0.35	84.27 ± 1.41	86.17 ± 2.67	21.51 ± 2.74	0.810 ± 0.019
	0.40	85.19 ± 0.92	87.16 ± 1.20	20.84 ± 2.88	0.788 ± 0.005
	0.45	60.62 ± 29.34	51.52 ± 42.07	11.60 ± 9.65	0.780 ± 0.002
	0.50	59.54 ± 28.47	50.58 ± 41.31	13.11 ± 11.07	0.786 ± 0.025
Gemma4-31B	0.00	89.17 ± 0.80	92.24 ± 1.11	18.25 ± 1.52	0.868 ± 0.015
	0.05	88.71 ± 1.02	90.83 ± 1.20	16.42 ± 0.86	0.807 ± 0.017
	0.10	88.46 ± 0.83	90.35 ± 1.87	16.08 ± 1.96	0.780 ± 0.012
	0.15	88.54 ± 0.68	91.38 ± 1.89	18.33 ± 3.11	0.758 ± 0.025
	0.20	88.54 ± 0.21	91.10 ± 1.18	17.67 ± 2.97	0.757 ± 0.019
	0.25	88.36 ± 0.44	90.90 ± 1.02	17.75 ± 2.76	0.740 ± 0.020
	0.30	87.02 ± 1.20	88.76 ± 1.35	17.17 ± 1.38	0.742 ± 0.004
	0.35	86.29 ± 1.16	88.69 ± 2.38	19.50 ± 2.10	0.740 ± 0.023
	0.40	75.41 ± 23.08	70.86 ± 35.44	13.58 ± 6.85	0.745 ± 0.016
	0.45	52.10 ± 27.96	35.03 ± 42.91	6.67 ± 8.20	0.729 ± 0.001
	0.50	29.27 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	–

Table 5: Raw multi-seed results behind Figure 3 on **InfoSeek** (Chen et al., 2023) test set. Values are mean ± std across 5 seeds.

Model	λ_{early}	Accuracy (%)	Failure Recall (%)	False Fire Rate (%)	Fire Depth
Qwen3-VL-8B	0.00	92.05 ± 0.46	91.64 ± 0.69	7.33 ± 0.20	0.881 ± 0.006
	0.05	91.45 ± 0.47	91.50 ± 0.94	8.61 ± 0.35	0.860 ± 0.014
	0.10	91.58 ± 0.36	91.44 ± 0.83	8.21 ± 0.37	0.829 ± 0.018
	0.15	90.76 ± 0.98	90.64 ± 2.15	9.06 ± 0.77	0.798 ± 0.012
	0.20	90.07 ± 0.47	89.99 ± 0.90	9.82 ± 0.42	0.777 ± 0.011
	0.25	89.22 ± 1.12	89.05 ± 2.47	10.53 ± 0.95	0.769 ± 0.012
	0.30	88.13 ± 0.85	87.84 ± 1.83	11.44 ± 0.96	0.748 ± 0.010
	0.35	88.33 ± 0.31	88.03 ± 0.84	11.25 ± 0.53	0.738 ± 0.003
	0.40	87.12 ± 0.36	86.69 ± 0.91	12.24 ± 0.62	0.729 ± 0.003
	0.45	86.30 ± 0.17	85.69 ± 0.50	12.80 ± 0.42	0.722 ± 0.001
	0.50	85.98 ± 0.44	84.94 ± 1.07	12.47 ± 0.57	0.723 ± 0.006
InternVL3.5-14B	0.00	88.94 ± 0.43	93.18 ± 0.66	24.00 ± 0.94	0.899 ± 0.007
	0.05	88.05 ± 0.77	92.62 ± 1.36	25.86 ± 1.16	0.886 ± 0.009
	0.10	88.52 ± 0.61	93.04 ± 0.99	25.24 ± 0.59	0.866 ± 0.010
	0.15	87.12 ± 0.42	91.50 ± 0.96	26.25 ± 1.49	0.849 ± 0.008
	0.20	86.08 ± 0.18	90.46 ± 0.32	27.26 ± 1.18	0.837 ± 0.008
	0.25	85.08 ± 0.57	89.36 ± 1.01	27.97 ± 1.09	0.809 ± 0.012
	0.30	85.50 ± 0.60	89.74 ± 0.75	27.43 ± 1.36	0.790 ± 0.007
	0.35	83.90 ± 0.61	87.66 ± 1.14	27.55 ± 1.12	0.785 ± 0.009
	0.40	83.03 ± 0.38	86.61 ± 0.59	27.89 ± 1.21	0.783 ± 0.004
	0.45	77.61 ± 12.36	78.65 ± 17.67	25.61 ± 3.97	0.774 ± 0.002
	0.50	76.54 ± 11.95	76.97 ± 17.31	24.77 ± 4.56	0.776 ± 0.010
Gemma4-31B	0.00	90.65 ± 0.29	93.55 ± 0.45	16.34 ± 0.66	0.869 ± 0.006
	0.05	90.83 ± 0.49	94.23 ± 0.61	17.37 ± 0.36	0.845 ± 0.008
	0.10	90.54 ± 0.37	93.82 ± 0.80	17.31 ± 0.80	0.802 ± 0.007
	0.15	89.76 ± 0.30	92.89 ± 0.91	17.79 ± 1.21	0.801 ± 0.011
	0.20	88.52 ± 0.15	91.54 ± 0.38	18.77 ± 1.26	0.779 ± 0.009
	0.25	89.06 ± 0.16	92.12 ± 0.48	18.34 ± 1.17	0.780 ± 0.010
	0.30	87.67 ± 0.47	90.49 ± 0.50	19.13 ± 0.67	0.750 ± 0.001
	0.35	87.16 ± 0.49	90.02 ± 0.98	19.71 ± 0.87	0.751 ± 0.011
	0.40	84.95 ± 9.62	86.79 ± 14.80	19.46 ± 2.90	0.751 ± 0.008
	0.45	80.27 ± 10.62	79.82 ± 16.48	18.65 ± 3.54	0.753 ± 0.002
	0.50	77.63 ± 0.09	75.30 ± 0.11	16.75 ± 0.08	0.737 ± 0.001

Table 6: Raw multi-seed results behind Figure 3 on **E-VQA** (Mensink et al., 2023) test set. Values are mean $\pm$ std across 5 seeds.

Model	λ_{early}	Accuracy (%)	Failure Recall (%)	False Fire Rate (%)	Fire Depth
Qwen3-VL-8B	0.00	72.72 ± 1.34	41.43 ± 8.75	8.47 ± 5.95	0.936 ± 0.013
	0.05	73.26 ± 1.56	48.98 ± 6.98	12.15 ± 5.41	0.918 ± 0.015
	0.10	73.03 ± 0.71	42.04 ± 7.23	8.34 ± 3.69	0.926 ± 0.030
	0.15	72.64 ± 1.50	39.59 ± 6.07	7.48 ± 4.20	0.922 ± 0.038
	0.20	73.18 ± 0.69	37.75 ± 1.83	5.52 ± 0.55	0.912 ± 0.022
	0.25	72.34 ± 0.29	40.00 ± 5.75	8.22 ± 3.73	0.891 ± 0.023
	0.30	71.80 ± 0.79	35.31 ± 8.63	6.26 ± 4.45	0.904 ± 0.028
	0.35	73.10 ± 0.61	36.12 ± 5.03	4.66 ± 2.15	0.879 ± 0.030
	0.40	73.03 ± 1.40	37.35 ± 4.11	5.52 ± 3.27	0.871 ± 0.015
	0.45	66.44 ± 4.89	12.45 ± 15.41	1.10 ± 1.66	0.880 ± 0.009
	0.50	62.45 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	–
InternVL3.5-14B	0.00	71.19 ± 0.56	43.33 ± 10.16	10.94 ± 5.66	0.978 ± 0.010
	0.05	70.57 ± 1.50	49.22 ± 6.66	15.72 ± 6.60	0.957 ± 0.014
	0.10	69.88 ± 0.79	55.10 ± 5.35	20.63 ± 4.39	0.935 ± 0.019
	0.15	70.65 ± 0.79	47.65 ± 4.90	14.59 ± 2.62	0.947 ± 0.027
	0.20	69.96 ± 1.53	48.63 ± 2.37	16.35 ± 3.88	0.953 ± 0.023
	0.25	70.34 ± 1.62	55.49 ± 6.19	20.13 ± 4.87	0.937 ± 0.013
	0.30	70.88 ± 0.42	47.65 ± 7.03	14.21 ± 4.71	0.942 ± 0.022
	0.35	69.73 ± 1.45	50.78 ± 3.24	18.11 ± 2.68	0.933 ± 0.014
	0.40	66.59 ± 4.67	32.55 ± 26.58	11.57 ± 9.48	0.931 ± 0.001
	0.45	64.60 ± 4.51	21.18 ± 26.05	7.55 ± 9.45	0.912 ± 0.002
	0.50	60.92 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	–
Gemma4-31B	0.00	77.70 ± 1.58	47.53 ± 2.49	5.60 ± 1.44	0.873 ± 0.027
	0.05	76.63 ± 1.33	47.96 ± 5.20	7.50 ± 1.67	0.841 ± 0.046
	0.10	75.86 ± 1.19	42.58 ± 4.74	5.71 ± 2.93	0.831 ± 0.036
	0.15	75.79 ± 0.29	44.30 ± 8.23	6.79 ± 4.27	0.805 ± 0.030
	0.20	73.87 ± 4.97	35.91 ± 18.34	5.12 ± 2.68	0.791 ± 0.012
	0.25	75.71 ± 1.42	46.45 ± 4.73	8.10 ± 2.25	0.787 ± 0.029
	0.30	73.26 ± 4.53	32.90 ± 16.75	4.40 ± 3.05	0.779 ± 0.032
	0.35	68.89 ± 5.54	20.00 ± 24.50	4.05 ± 4.96	0.717 ± 0.009
	0.40	69.04 ± 5.74	17.85 ± 22.07	2.62 ± 3.40	0.725 ± 0.007
	0.45	64.37 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	–
	0.50	64.37 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	–

Table 7: Raw multi-seed numbers behind the RQ1 hazard panels on **VISA** (Ma et al., 2025) test set with three candidates. Values are mean $\pm$ std across 5 seeds.

Model	Method	Metric	λ_{early}										
			0.00	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
Qwen3-VL	FTT	Acc	$91.9_{\pm 0.6}$	$90.6_{\pm 2.2}$	$90.7_{\pm 1.1}$	$89.7_{\pm 1.1}$	$90.6_{\pm 0.5}$	$89.2_{\pm 1.5}$	$89.7_{\pm 1.1}$	$88.2_{\pm 2.6}$	$88.2_{\pm 1.2}$	$84.7_{\pm 4.7}$	$84.9_{\pm 1.8}$
		Comp Rec	$93.7_{\pm 1.1}$	$92.6_{\pm 1.9}$	$92.1_{\pm 1.9}$	$92.4_{\pm 1.6}$	$92.2_{\pm 1.0}$	$90.1_{\pm 1.9}$	$90.7_{\pm 2.2}$	$89.0_{\pm 2.6}$	$89.2_{\pm 1.4}$	$84.2_{\pm 5.0}$	$84.7_{\pm 3.2}$
		Dist Rec	$78.4_{\pm 1.5}$	$74.5_{\pm 8.1}$	$76.5_{\pm 3.7}$	$70.0_{\pm 5.6}$	$76.2_{\pm 1.6}$	$73.6_{\pm 5.9}$	$74.6_{\pm 2.4}$	$70.4_{\pm 9.2}$	$69.2_{\pm 7.1}$	$64.7_{\pm 11.3}$	$61.1_{\pm 2.9}$
	D3C	Acc	$83.6_{\pm 2.1}$	$83.0_{\pm 1.6}$	$83.1_{\pm 1.2}$	$82.7_{\pm 1.4}$	$83.3_{\pm 0.8}$	$83.1_{\pm 0.5}$	$82.6_{\pm 1.2}$	$82.7_{\pm 0.6}$	$82.1_{\pm 0.7}$	$81.7_{\pm 0.9}$	$81.2_{\pm 0.4}$
		Comp Rec	$86.1_{\pm 1.5}$	$84.7_{\pm 1.7}$	$84.2_{\pm 1.3}$	$83.1_{\pm 0.8}$	$85.0_{\pm 1.5}$	$83.5_{\pm 1.1}$	$85.0_{\pm 0.5}$	$83.1_{\pm 1.4}$	$82.5_{\pm 1.3}$	$81.5_{\pm 1.7}$	$80.8_{\pm 0.4}$
		Dist Rec	$56.7_{\pm 7.6}$	$55.5_{\pm 7.7}$	$56.5_{\pm 5.0}$	$56.0_{\pm 8.5}$	$55.7_{\pm 7.8}$	$59.5_{\pm 2.3}$	$54.4_{\pm 7.9}$	$57.2_{\pm 1.2}$	$57.8_{\pm 3.3}$	$55.7_{\pm 3.4}$	$54.6_{\pm 2.3}$
InternVL3.5	FTT	Acc	$87.6_{\pm 2.7}$	$87.2_{\pm 1.4}$	$87.7_{\pm 1.0}$	$86.2_{\pm 3.0}$	$85.9_{\pm 1.2}$	$85.3_{\pm 1.8}$	$79.9_{\pm 1.5}$	$79.7_{\pm 1.2}$	$79.0_{\pm 1.9}$	$77.5_{\pm 2.3}$	$76.0_{\pm 2.9}$
		Comp Rec	$93.3_{\pm 1.4}$	$92.6_{\pm 1.3}$	$92.5_{\pm 1.7}$	$91.9_{\pm 2.6}$	$90.1_{\pm 2.3}$	$89.6_{\pm 2.2}$	$88.6_{\pm 1.4}$	$88.2_{\pm 3.6}$	$88.2_{\pm 2.6}$	$86.6_{\pm 3.2}$	$83.4_{\pm 3.1}$
		Dist Rec	$76.4_{\pm 10.4}$	$74.9_{\pm 5.3}$	$78.4_{\pm 3.3}$	$72.3_{\pm 9.6}$	$76.3_{\pm 4.0}$	$75.6_{\pm 5.5}$	$53.2_{\pm 6.4}$	$51.7_{\pm 6.6}$	$50.0_{\pm 8.9}$	$46.4_{\pm 4.5}$	$46.7_{\pm 8.5}$
	D3C	Acc	$78.9_{\pm 1.1}$	$78.1_{\pm 0.4}$	$77.5_{\pm 0.7}$	$77.3_{\pm 0.9}$	$77.7_{\pm 0.9}$	$77.8_{\pm 0.7}$	$77.9_{\pm 0.3}$	$76.9_{\pm 0.9}$	$77.3_{\pm 0.9}$	$77.1_{\pm 0.7}$	$76.5_{\pm 1.0}$
		Comp Rec	$86.2_{\pm 1.2}$	$90.9_{\pm 1.1}$	$89.3_{\pm 2.6}$	$87.9_{\pm 2.2}$	$88.3_{\pm 2.3}$	$87.7_{\pm 1.5}$	$88.3_{\pm 0.9}$	$87.8_{\pm 1.3}$	$88.5_{\pm 0.2}$	$88.0_{\pm 2.4}$	$85.8_{\pm 1.4}$
		Dist Rec	$54.1_{\pm 6.3}$	$40.8_{\pm 4.3}$	$42.3_{\pm 7.7}$	$46.4_{\pm 5.2}$	$43.5_{\pm 4.6}$	$47.2_{\pm 6.1}$	$45.7_{\pm 1.8}$	$41.4_{\pm 5.5}$	$40.9_{\pm 4.6}$	$40.4_{\pm 8.1}$	$42.8_{\pm 6.6}$
Gemma4	FTT	Acc	$83.5_{\pm 0.5}$	$83.8_{\pm 0.5}$	$82.9_{\pm 0.6}$	$83.2_{\pm 0.8}$	$82.2_{\pm 1.1}$	$82.2_{\pm 0.9}$	$81.4_{\pm 0.6}$	$81.8_{\pm 0.4}$	$81.0_{\pm 1.0}$	$80.4_{\pm 0.7}$	$80.3_{\pm 0.7}$
		Comp Rec	$86.7_{\pm 1.2}$	$88.9_{\pm 1.4}$	$85.5_{\pm 2.4}$	$86.5_{\pm 1.6}$	$83.8_{\pm 2.3}$	$85.0_{\pm 1.5}$	$83.4_{\pm 2.1}$	$84.4_{\pm 1.7}$	$82.0_{\pm 2.0}$	$83.2_{\pm 2.3}$	$82.5_{\pm 1.6}$
		Dist Rec	$62.9_{\pm 4.3}$	$57.0_{\pm 4.9}$	$62.3_{\pm 5.7}$	$58.5_{\pm 3.3}$	$61.8_{\pm 3.6}$	$60.4_{\pm 0.6}$	$57.9_{\pm 4.4}$	$59.2_{\pm 2.8}$	$58.6_{\pm 3.0}$	$49.3_{\pm 6.5}$	$53.0_{\pm 6.5}$
	D3C	Acc	$81.7_{\pm 1.4}$	$82.3_{\pm 1.0}$	$81.7_{\pm 0.5}$	$81.0_{\pm 0.9}$	$80.9_{\pm 1.5}$	$81.4_{\pm 1.0}$	$81.1_{\pm 1.4}$	$81.0_{\pm 0.2}$	$78.7_{\pm 3.0}$	$79.8_{\pm 0.6}$	$80.6_{\pm 0.4}$
		Comp Rec	$81.8_{\pm 3.7}$	$83.2_{\pm 1.1}$	$82.1_{\pm 1.8}$	$80.2_{\pm 1.6}$	$80.1_{\pm 3.3}$	$81.4_{\pm 3.1}$	$81.3_{\pm 3.2}$	$79.8_{\pm 0.6}$	$77.9_{\pm 6.8}$	$77.7_{\pm 0.6}$	$81.0_{\pm 1.6}$
		Dist Rec	$65.3_{\pm 3.9}$	$62.9_{\pm 4.1}$	$60.9_{\pm 8.0}$	$65.7_{\pm 5.1}$	$63.8_{\pm 7.2}$	$63.5_{\pm 7.6}$	$59.1_{\pm 8.6}$	$64.9_{\pm 4.0}$	$56.3_{\pm 11.9}$	$63.3_{\pm 7.2}$	$58.9_{\pm 4.7}$

Table 8: Values plotted in Figure 4 for **InfoSeek**. Each cell is $\text{mean}_{\pm \text{std}}$ across five seeds.

Model	Method	Metric	λ_{early}										
			0.00	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
Qwen3-VL	FTT	Acc	$92.3_{\pm 0.6}$	$91.6_{\pm 2.3}$	$91.8_{\pm 1.1}$	$90.8_{\pm 1.1}$	$89.6_{\pm 0.6}$	$88.2_{\pm 1.5}$	$86.5_{\pm 1.0}$	$86.9_{\pm 2.6}$	$84.8_{\pm 1.2}$	$83.0_{\pm 4.7}$	$81.8_{\pm 1.9}$
		Comp Rec	$93.9_{\pm 1.1}$	$94.6_{\pm 1.8}$	$94.5_{\pm 1.9}$	$93.8_{\pm 1.6}$	$92.9_{\pm 1.1}$	$91.8_{\pm 1.9}$	$90.7_{\pm 2.2}$	$91.2_{\pm 2.6}$	$89.5_{\pm 1.4}$	$87.7_{\pm 5.1}$	$85.6_{\pm 3.2}$
		Dist Rec	$80.0_{\pm 1.5}$	$77.7_{\pm 8.3}$	$78.6_{\pm 3.3}$	$76.4_{\pm 5.7}$	$74.0_{\pm 1.7}$	$71.5_{\pm 5.8}$	$67.5_{\pm 2.4}$	$68.1_{\pm 9.1}$	$63.8_{\pm 7.1}$	$60.1_{\pm 11.0}$	$58.2_{\pm 3.0}$
	D3C	Acc	$83.8_{\pm 2.1}$	$84.3_{\pm 1.6}$	$84.1_{\pm 1.3}$	$83.5_{\pm 1.4}$	$82.7_{\pm 0.8}$	$81.9_{\pm 0.6}$	$82.1_{\pm 1.3}$	$81.4_{\pm 0.6}$	$80.2_{\pm 0.7}$	$79.3_{\pm 0.9}$	$79.0_{\pm 0.4}$
		Comp Rec	$85.8_{\pm 1.5}$	$86.5_{\pm 1.7}$	$86.2_{\pm 1.4}$	$85.6_{\pm 0.9}$	$84.9_{\pm 1.5}$	$84.2_{\pm 1.3}$	$84.3_{\pm 0.5}$	$84.5_{\pm 1.4}$	$83.2_{\pm 1.3}$	$82.3_{\pm 1.7}$	$81.5_{\pm 0.5}$
		Dist Rec	$57.4_{\pm 7.5}$	$61.0_{\pm 7.7}$	$59.5_{\pm 5.1}$	$57.6_{\pm 8.5}$	$56.1_{\pm 7.6}$	$54.5_{\pm 2.4}$	$55.0_{\pm 8.2}$	$53.0_{\pm 1.1}$	$50.9_{\pm 3.4}$	$49.0_{\pm 3.4}$	$48.4_{\pm 2.2}$
InternVL3.5	FTT	Acc	$88.8_{\pm 2.6}$	$87.2_{\pm 1.3}$	$88.0_{\pm 1.1}$	$86.0_{\pm 3.0}$	$84.1_{\pm 1.2}$	$82.7_{\pm 1.8}$	$83.1_{\pm 1.5}$	$80.0_{\pm 1.2}$	$77.8_{\pm 1.8}$	$76.0_{\pm 2.2}$	$74.8_{\pm 2.9}$
		Comp Rec	$94.2_{\pm 1.4}$	$93.9_{\pm 1.3}$	$94.2_{\pm 1.8}$	$93.0_{\pm 2.6}$	$91.9_{\pm 2.4}$	$90.6_{\pm 2.4}$	$90.6_{\pm 1.3}$	$88.1_{\pm 3.6}$	$86.1_{\pm 2.5}$	$84.6_{\pm 3.3}$	$83.0_{\pm 3.1}$
		Dist Rec	$78.7_{\pm 10.3}$	$74.2_{\pm 5.4}$	$76.5_{\pm 3.2}$	$71.6_{\pm 9.8}$	$67.5_{\pm 3.8}$	$65.2_{\pm 5.5}$	$66.4_{\pm 6.6}$	$60.2_{\pm 6.7}$	$56.5_{\pm 8.9}$	$53.3_{\pm 4.4}$	$51.0_{\pm 8.4}$
	D3C	Acc	$79.5_{\pm 1.1}$	$78.4_{\pm 0.5}$	$77.5_{\pm 0.6}$	$77.8_{\pm 0.9}$	$78.3_{\pm 0.9}$	$77.1_{\pm 0.7}$	$76.4_{\pm 0.4}$	$75.5_{\pm 0.9}$	$75.8_{\pm 0.9}$	$74.2_{\pm 0.7}$	$73.5_{\pm 1.0}$
		Comp Rec	$89.4_{\pm 1.3}$	$89.3_{\pm 1.1}$	$89.1_{\pm 2.7}$	$88.6_{\pm 2.2}$	$88.3_{\pm 2.4}$	$88.4_{\pm 1.4}$	$88.3_{\pm 0.8}$	$87.6_{\pm 1.3}$	$87.6_{\pm 0.2}$	$86.2_{\pm 2.5}$	$85.2_{\pm 1.4}$
		Dist Rec	$49.3_{\pm 6.0}$	$46.4_{\pm 4.4}$	$44.2_{\pm 7.7}$	$45.8_{\pm 5.2}$	$47.7_{\pm 4.7}$	$43.8_{\pm 5.9}$	$42.0_{\pm 1.8}$	$40.7_{\pm 5.5}$	$41.5_{\pm 4.6}$	$39.3_{\pm 8.1}$	$38.8_{\pm 6.7}$
Gemma4	FTT	Acc	$84.0_{\pm 0.4}$	$84.9_{\pm 0.6}$	$84.2_{\pm 0.6}$	$83.5_{\pm 0.8}$	$82.0_{\pm 1.0}$	$82.7_{\pm 0.9}$	$80.8_{\pm 0.6}$	$80.2_{\pm 0.5}$	$78.6_{\pm 1.0}$	$76.8_{\pm 0.7}$	$77.3_{\pm 0.6}$
		Comp Rec	$87.5_{\pm 1.2}$	$88.6_{\pm 1.4}$	$87.7_{\pm 2.5}$	$87.5_{\pm 1.6}$	$86.2_{\pm 2.2}$	$86.7_{\pm 1.5}$	$85.0_{\pm 2.1}$	$84.5_{\pm 1.7}$	$82.9_{\pm 2.0}$	$81.3_{\pm 2.4}$	$81.7_{\pm 1.5}$
		Dist Rec	$62.5_{\pm 4.5}$	$66.2_{\pm 5.1}$	$64.3_{\pm 5.6}$	$62.5_{\pm 3.3}$	$59.3_{\pm 3.2}$	$61.0_{\pm 0.8}$	$56.7_{\pm 4.3}$	$55.6_{\pm 2.9}$	$52.7_{\pm 3.4}$	$48.4_{\pm 6.3}$	$49.6_{\pm 6.3}$
	D3C	Acc	$82.4_{\pm 1.4}$	$83.5_{\pm 1.0}$	$83.0_{\pm 0.5}$	$81.8_{\pm 0.9}$	$80.9_{\pm 1.6}$	$81.5_{\pm 1.0}$	$80.8_{\pm 1.4}$	$79.3_{\pm 0.3}$	$78.0_{\pm 2.9}$	$77.8_{\pm 0.6}$	$76.6_{\pm 0.4}$
		Comp Rec	$82.9_{\pm 3.8}$	$84.2_{\pm 1.1}$	$84.0_{\pm 1.8}$	$82.4_{\pm 1.7}$	$81.8_{\pm 3.4}$	$82.6_{\pm 3.1}$	$82.3_{\pm 3.1}$	$81.2_{\pm 0.7}$	$80.0_{\pm 6.7}$	$79.0_{\pm 0.6}$	$78.2_{\pm 1.6}$
		Dist Rec	$63.2_{\pm 4.0}$	$68.0_{\pm 4.3}$	$65.1_{\pm 7.9}$	$61.6_{\pm 4.9}$	$59.4_{\pm 7.4}$	$62.1_{\pm 7.7}$	$58.3_{\pm 8.3}$	$55.0_{\pm 4.0}$	$52.1_{\pm 12.2}$	$53.1_{\pm 7.1}$	$49.9_{\pm 4.7}$

Table 9: Values plotted in Figure 4 for **E-VQA**. Each cell is $\text{mean}_{\pm \text{std}}$ across five seeds.

Model	Method	Metric	λ_{early}										
			0.00	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50
Qwen3-VL	FTT	Acc	$74.1_{\pm 0.4}$	$73.7_{\pm 1.3}$	$73.4_{\pm 1.0}$	$74.2_{\pm 0.9}$	$73.3_{\pm 1.3}$	$72.5_{\pm 1.1}$	$74.0_{\pm 0.8}$	$73.4_{\pm 1.3}$	$73.0_{\pm 0.5}$	$72.2_{\pm 0.7}$	$73.3_{\pm 1.0}$
		Comp Rec	$48.4_{\pm 5.6}$	$45.0_{\pm 7.4}$	$46.2_{\pm 12.5}$	$41.5_{\pm 4.0}$	$47.1_{\pm 4.0}$	$42.3_{\pm 7.3}$	$43.0_{\pm 5.5}$	$48.9_{\pm 5.8}$	$40.6_{\pm 6.8}$	$44.0_{\pm 5.8}$	$40.8_{\pm 2.6}$
		Dist Rec	$11.8_{\pm 4.7}$	$10.5_{\pm 5.0}$	$10.5_{\pm 3.1}$	$8.0_{\pm 2.5}$	$6.8_{\pm 0.0}$	$9.2_{\pm 3.1}$	$6.8_{\pm 0.0}$	$9.2_{\pm 3.1}$	$11.8_{\pm 7.3}$	$6.8_{\pm 0.0}$	$6.8_{\pm 0.0}$
	D3C	Acc	$69.5_{\pm 1.3}$	$68.9_{\pm 1.2}$	$70.4_{\pm 0.5}$	$69.5_{\pm 1.5}$	$67.7_{\pm 1.3}$	$69.0_{\pm 0.8}$	$68.6_{\pm 1.3}$	$68.7_{\pm 0.7}$	$69.9_{\pm 0.7}$	$68.7_{\pm 2.0}$	$68.6_{\pm 2.5}$
		Comp Rec	$37.3_{\pm 4.1}$	$39.5_{\pm 9.2}$	$37.1_{\pm 3.3}$	$37.3_{\pm 6.8}$	$29.5_{\pm 8.6}$	$34.6_{\pm 7.4}$	$36.1_{\pm 7.5}$	$33.7_{\pm 7.4}$	$31.7_{\pm 1.1}$	$34.9_{\pm 5.6}$	$37.8_{\pm 4.6}$
		Dist Rec	$2.5_{\pm 3.1}$	$0.0_{\pm 0.0}$	$3.8_{\pm 5.0}$	$2.5_{\pm 3.1}$	$1.2_{\pm 2.5}$	$0.0_{\pm 0.0}$	$1.2_{\pm 2.5}$	$1.2_{\pm 2.5}$	$0.0_{\pm 0.0}$	$3.8_{\pm 3.1}$	$1.2_{\pm 2.5}$
InternVL3.5	FTT	Acc	$69.5_{\pm 2.0}$	$70.2_{\pm 1.3}$	$69.2_{\pm 0.8}$	$67.7_{\pm 1.0}$	$69.6_{\pm 1.7}$	$68.7_{\pm 1.0}$	$68.0_{\pm 0.5}$	$69.3_{\pm 1.4}$	$69.3_{\pm 1.0}$	$69.9_{\pm 0.4}$	$70.2_{\pm 1.6}$
		Comp Rec	$52.0_{\pm 11.5}$	$54.9_{\pm 6.4}$	$38.1_{\pm 5.3}$	$53.4_{\pm 18.6}$	$51.1_{\pm 11.9}$	$51.7_{\pm 17.7}$	$53.4_{\pm 20.6}$	$47.1_{\pm 12.3}$	$43.6_{\pm 13.4}$	$58.1_{\pm 3.6}$	$56.9_{\pm 14.5}$
		Dist Rec	$29.1_{\pm 8.5}$	$25.4_{\pm 10.0}$	$29.7_{\pm 11.3}$	$33.3_{\pm 10.0}$	$27.8_{\pm 12.1}$	$27.8_{\pm 2.7}$	$30.3_{\pm 3.5}$	$23.6_{\pm 9.7}$	$25.4_{\pm 7.0}$	$25.4_{\pm 7.0}$	$27.8_{\pm 5.1}$
	D3C	Acc	$63.9_{\pm 0.8}$	$64.2_{\pm 2.7}$	$64.2_{\pm 1.5}$	$63.8_{\pm 1.1}$	$65.3_{\pm 2.0}$	$65.4_{\pm 0.9}$	$64.2_{\pm 0.7}$	$64.9_{\pm 1.7}$	$66.3_{\pm 2.0}$	$64.6_{\pm 1.8}$	$66.1_{\pm 1.2}$
		Comp Rec	$20.0_{\pm 11.9}$	$26.1_{\pm 11.0}$	$35.1_{\pm 13.6}$	$27.2_{\pm 16.1}$	$24.6_{\pm 11.6}$	$33.3_{\pm 7.9}$	$34.2_{\pm 9.6}$	$29.0_{\pm 15.1}$	$27.2_{\pm 3.7}$	$30.1_{\pm 13.6}$	$21.2_{\pm 10.9}$
		Dist Rec	$24.9_{\pm 11.1}$	$19.4_{\pm 7.3}$	$24.9_{\pm 4.8}$	$22.4_{\pm 4.9}$	$22.4_{\pm 5.9}$	$14.5_{\pm 6.5}$	$18.8_{\pm 7.3}$	$17.6_{\pm 9.7}$	$18.8_{\pm 6.2}$	$22.4_{\pm 7.3}$	$22.4_{\pm 9.7}$
Gemma4	FTT	Acc	$78.8_{\pm 3.7}$	$80.4_{\pm 2.6}$	$79.4_{\pm 1.7}$	$79.5_{\pm 2.4}$	$78.1_{\pm 2.5}$	$77.6_{\pm 1.3}$	$77.4_{\pm 2.8}$	$73.8_{\pm 4.0}$	$73.3_{\pm 4.2}$	$72.8_{\pm 4.7}$	$70.2_{\pm 2.4}$
		Comp Rec	$56.8_{\pm 16.4}$	$63.3_{\pm 11.6}$	$60.8_{\pm 9.6}$	$59.9_{\pm 10.3}$	$57.0_{\pm 14.9}$	$51.4_{\pm 7.9}$	$49.6_{\pm 10.8}$	$39.7_{\pm 15.8}$	$38.1_{\pm 16.0}$	$35.4_{\pm 16.0}$	$26.2_{\pm 6.7}$
		Dist Rec	$54.0_{\pm 10.0}$	$44.0_{\pm 18.7}$	$44.0_{\pm 24.5}$	$49.0_{\pm 15.8}$	$29.0_{\pm 10.0}$	$39.0_{\pm 20.0}$	$29.0_{\pm 10.0}$	$44.0_{\pm 24.5}$	$34.0_{\pm 20.0}$	$24.0_{\pm 0.0}$	$24.0_{\pm 0.0}$
	D3C	Acc	$73.7_{\pm 0.5}$	$72.9_{\pm 1.5}$	$74.2_{\pm 0.6}$	$72.5_{\pm 1.2}$	$71.5_{\pm 1.8}$	$72.5_{\pm 1.6}$	$73.7_{\pm 0.6}$	$72.2_{\pm 2.0}$	$71.3_{\pm 1.9}$	$70.2_{\pm 4.1}$	$71.2_{\pm 2.5}$
		Comp Rec	$39.5_{\pm 4.6}$	$39.3_{\pm 4.9}$	$43.1_{\pm 1.8}$	$36.4_{\pm 9.5}$	$29.9_{\pm 12.9}$	$34.8_{\pm 9.6}$	$42.7_{\pm 2.9}$	$31.7_{\pm 9.9}$	$27.4_{\pm 10.9}$	$23.8_{\pm 16.0}$	$27.2_{\pm 12.2}$
		Dist Rec	$20.0_{\pm 10.0}$	$30.0_{\pm 10.0}$	$10.0_{\pm 12.2}$	$20.0_{\pm 18.7}$	$30.0_{\pm 18.7}$	$30.0_{\pm 10.0}$	$15.0_{\pm 12.2}$	$5.0_{\pm 10.0}$	$10.0_{\pm 12.2}$	$5.0_{\pm 10.0}$	$10.0_{\pm 12.2}$

Table 10: Values plotted in Figure 4 for **VISA**. Each cell is $\text{mean}_{\pm \text{std}}$ across five seeds.