

ReCALL: Recalibrating Capability Degradation for MLLM-based Composed Image Retrieval

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Abstract

*Composed Image Retrieval (CIR) aims to retrieve target images based on a hybrid query comprising a reference image and a modification text. Early dual-tower Vision-Language Models (VLMs) struggle with cross-modality compositional reasoning required for this task. Recently, adapting generative Multimodal Large Language Models (MLLMs) for retrieval offers a promising direction. However, we identify that this adaptation strategy overlooks a fundamental issue: adapting a generative MLLM into a single-embedding discriminative retriever triggers a paradigm conflict, which leads to **Capability Degradation**—the deterioration of native fine-grained reasoning after retrieval adaptation. To address this challenge, we propose **ReCALL** (Recalibrating Capability Degradation), a model-agnostic framework that follows a diagnose–generate–refine pipeline: Firstly, we diagnose cognitive blind spots of the retriever via self-guided informative instance mining. Next, we generate corrective instructions and triplets by CoT prompting the foundation MLLM and conduct quality control with VQA-based consistency filtering. Finally, we refine the retriever through continual training on these triplets with a grouped contrastive scheme, thereby internalizing fine-grained visual–semantic distinctions and realigning the discriminative embedding space of retriever with intrinsic compositional reasoning within the MLLM. Extensive experiments on CIRR and FashionIQ show that ReCALL consistently recalibrates degraded capabilities and achieves state-of-the-art performance. Code will be released soon.*

1. Introduction

Composed Image Retrieval (CIR) retrieves a target image given a composed query that combines a reference image and a textual modification. Due to the vast application potential in domains such as e-commerce and design, it has attracted a surge of research interests [6, 49, 53] recently, enabling users to articulate more complex and precise search intent compared with traditional image retrieval [14, 34, 58, 59].

Early dual-tower vision–language models (VLMs) [1, 4, 6, 23, 29] struggle with fine-grained compositional reasoning because of shallow cross-modal alignment and limited modality interaction. In contrast, Multimodal Large Language Models (MLLMs) [2, 3, 31, 50, 57, 62], benefiting from deep-fusion architectures and robust instruction-following abilities, are naturally suited for CIR. Recent works therefore adapt MLLMs to retrieval via contrastive learning [20, 26, 28]. Despite the remarkable progress, we identify a critical and overlooked challenge: adapting the MLLM’s native generative paradigm (focusing on step-wise reasoning) into a single-embedding discriminative paradigm (highlighting on vector similarity) introduces an intrinsic paradigm conflict. This conflict fundamentally degrades the model’s compositional reasoning capabilities, particularly in fine-grained grounding and relational understanding.

To substantiate the Capability Degradation phenomenon, we conduct both qualitative and quantitative analysis, comparing the Foundation MLLM (\mathcal{F}) under its native generative mode with its fine-tuned retrieval counterpart ($\mathcal{R}_{\text{base}}$). As illustrated in Fig. 1 (Left), for a challenging query, the base retriever $\mathcal{R}_{\text{base}}$ fails to retrieve the target, while the foundation model \mathcal{F} succeeds via zero-shot VQA. This



Figure 1. Empirical illustration of Capability Degradation and the effectiveness of ReCALL ($\mathcal{R}_{\text{refine}}$). (a) We compare the Foundation MLLM (\mathcal{F}) under its native VQA-based generative paradigm with its fine-tuned retrieval counterpart ($\mathcal{R}_{\text{base}}$) under a similarity-based discriminative paradigm using a challenging query that requires fine-grained reasoning. The base retriever $\mathcal{R}_{\text{base}}$ fails due to fine-grained grounding errors, while \mathcal{F} succeeds through step-wise reasoning. (b) Quantitative evidence of Capability Degradation and Recalibrate. We test $\mathcal{R}_{\text{base}}$ on a subset of 1k instances where \mathcal{F} successfully retrieves the target (i.e., \mathcal{F} achieves 100% R@1). The low R@1 performance of $\mathcal{R}_{\text{base}}$ (only 62.33% on CIRR and 55.80% on FashionIQ) on this \mathcal{F} -solvable subset provides quantifiable proof of capability degradation. Our proposed ReCALL framework effectively recovers the lost abilities, boosting the performance of $\mathcal{R}_{\text{base}}$ to $\mathcal{R}_{\text{refine}}$, with significant gains.

qualitative contrast highlights how \mathcal{F} 's intrinsic compositional reasoning is suppressed, with the quantitative evidence in Fig. 1 (Right). Crucially, $\mathcal{R}_{\text{base}}$ exhibits severely degraded performance, achieving only 62.33% and 55.80% R@1 on CIRR and FashionIQ, respectively, on this \mathcal{F} -solvable subset, which unequivocally quantifies the extent of capability degradation.

To address this issue, we propose **ReCALL**, a model-agnostic framework that recalibrates degraded capabilities from the foundation model and internalizes them into the retriever's representations. Our core idea is to leverage the MLLM's stepwise “native” reasoning signals to supervise the “foreign” single-embedding retrieval space, within a **diagnose–generate–refine** pipeline. Toward this end, we first **diagnose** the retrieval model’s cognitive blind spots through a self-guided informative instance mining procedure, which autonomously discovers samples that the retrieval model currently struggles to distinguish. Next, we aim to **generate** corrective supervision that explicitly targets these deficiencies. Specifically, we prompt the foundation model with Chain-of-Thought (CoT) [10, 27, 41, 44, 60] to generate high-quality, *corrective* textual instructions for the hard samples, forming new triplets. These triplets exhibit subtle but semantically meaningful variations across both visual and textual modalities, precisely capturing the nuances that the retrieval model previously failed to distinguish. Crucially, to ensure the reliability of these generated signals, we incorporate a VQA-based consistency check to filter out noise. Finally, we **refine** the retrieval model through a novel Grouped Contrastive Learning strategy. By constructing training batches that explicitly contrast the original queries with their corrected counterparts, we encourage

the model to internalize these fine-grained visual–semantic distinctions, thereby realigning its discriminative representation space with the foundation model’s intrinsic compositional reasoning capabilities.

In summary, our main contributions are as follows:

- We identify a critical challenge in adapting MLLMs to CIR, termed Capability Degradation, where models’ native compositional reasoning abilities deteriorate during retrieval-oriented fine-tuning.
- We propose a model-agnostic framework, **ReCALL**, to recalibrate the embedding space of the retriever with the MLLM’s compositional reasoning through a *diagnose–generate–refine* pipeline.
- Extensive experiments demonstrate that ReCALL effectively recalibrates the degraded capabilities, ultimately achieving state-of-the-art performance on mainstream CIR benchmarks, including CIRR [29] and FashionIQ [55].

2. Related Work

2.1. Composed Image Retrieval

CIR aims to retrieve a target image based on a hybrid-modal query. Early approaches [6, 7, 12, 29] primarily follow the VLM framework (*e.g.*, CLIP [35]), lacking through fusion between query modalities. They resort to external fusion modules [5, 8, 22, 23, 29, 30, 53] or concatenation via pseudo-tokens [4, 11, 13, 36, 45], but constrained by a fundamental architectural flaw, *i.e.*, shallow alignment. [17, 54] To overcome it, recent research has shifted towards MLLMs, with CIR-LVLM [42] as a representative example that leverages an LVLM as a user-intent-aware encoder for CIR. Benefiting from deep fusion and instruction-

following, such adaptations have consistently demonstrated superior performance on mainstream benchmarks. Despite the remarkable progress, we argue that their adaptation for discriminative retrieval can introduce *Capability Degradation*. This conflict leads to the degradation of the model’s native fine-grained reasoning, a critical gap our work aims to address.

2.2. Self-Improvement for MLLMs

Self-improvement has proved effective for large language models: STaR bootstraps from model-produced rationales to reinforce correct reasoning [61], while Reflexion and Self-Refine introduce explicit self-feedback loops to iteratively revise and correct outputs [32, 38]. In contrast, contemporary CIR adaptations of MLLMs predominantly adopt a *single-stage, static fine-tuning* paradigm—fine-tuning unified encoders on curated benchmarks without online diagnosis-and-repair [20, 26, 28, 42]. Building on this gap, **ReCALL** instantiates a retrieval-oriented self-improvement loop aligned with our *diagnose–generate–refine* pipeline.

3. Method

This section outlines the ReCALL framework. As shown in Fig. 2, we first formalize the task and introduce the model components (Sec. 3.1), then describe the baseline adaptation procedure (Sec. 3.2). We next present the diagnose–generate–refine pipeline, including self-guided informative instance mining (Sec. 3.3), generative calibration (Sec. 3.4), and targeted refinement (Sec. 3.5).

3.1. Problem Formulation

CIR is defined as follows: given a reference image I_r and a modification text T_m , the goal is to retrieve the target image I_t from a large gallery. We introduce the following model entities used throughout this work:

- **Foundation Model (\mathcal{F}):** An MLLM with strong generative and reasoning capabilities, providing the intrinsic compositional reasoning that our framework leverages.
- **Baseline Retrieval Model (\mathcal{R}_{base}):** A retrieval model fine-tuned from \mathcal{F} on CIR triplets using contrastive learning. While it offers basic retrieval performance, it still suffers from capability degradation described in Sec. 1. This model serves as the starting point for our diagnose–generate–refine pipeline.
- **Refined Model (\mathcal{R}_{refine}):** The final model variant of our framework. It addresses the capability degradation in \mathcal{R}_{base} by absorbing the compositional reasoning of \mathcal{F} , yielding a recalibrated and more robust retriever.

3.2. Stage 1: Baseline Retrieval Model Adaptation

The first stage adapts \mathcal{F} into a retrieval model to attain basic discriminative ability, yielding the baseline retriever

(\mathcal{R}_{base}). It provides a stable starting point for the subsequent diagnose–generate–refine pipeline.

To maximize retention of pre-trained knowledge, \mathcal{R}_{base} is initialized directly from \mathcal{F} . We then fine-tune the model on CIR triplets (I_r, T_m, I_t) via InfoNCE [33], encouraging the query representation z_q to align with its positive target z_t while pushing away in-batch negatives.

While this learning process yields a functional retriever, it also suffers from capability degradation, *i.e.*, discriminative fine-tuning may compromise the fine-grained compositional reasoning within \mathcal{F} . To deal with it, the following diagnose stage of ReCALL is explicitly designed to detect and remediate these consequent blind spots.

3.3. Stage 2: Self-Guided Informative Instance Mining

To effectively recalibrate \mathcal{R}_{base} , we introduce a self-guided informative instance mining strategy to probe the decision boundaries of \mathcal{R}_{base} that are most susceptible to the capability degradation discussed in Sec. 1.

First, we perform retrieval inference on the training set using \mathcal{R}_{base} . We exclude queries where the ground-truth I_t is successfully ranked first, assuming these instances reflect sufficient discriminative power. Instead, we focus specifically on the failure cases, as they likely harbor the most informative signals regarding where the fine-tuning process has compromised the model’s original reasoning capabilities.

For each failure case, we define the hard-negative set $\{I_h\}$ by selecting the **top- K** images ranked above I_t . These high-confidence distractors share subtle visual or semantic nuances with the ground truth, deceiving the retriever due to the degradation of its fine-grained discriminative and compositional reasoning. Consequently, these specific failure cases serve as critical anchors for the subsequent calibration stage, as they pinpoint exactly where the model’s decision boundary needs to be refined.

3.4. Stage 3: Generative Calibration

Given the hard negatives $\{I_h\}$ identified in Sec. 3.3, we exploit the intrinsic generative and reasoning capabilities of \mathcal{F} to synthesize corrective supervision signals. The goal is to articulate how the original instruction T_m should be *minimally* adjusted so that it aligns with each hard negative I_h , effectively transforming a failure case into a high-quality training example.

CoT-Assisted Generation. In general, a hard negative sample I_h differs from the ground-truth I_t only in subtle visual aspects, as shown in Fig. 2. Such subtle differences exactly reflect the discriminative weaknesses of \mathcal{R}_{base} , which could be repurposed into informative supervision for continual learning. To achieve this goal, we construct minimal edits to T_m and obtain \tilde{T}_m that precisely reflect the visual discrepancies between I_h and I_t .

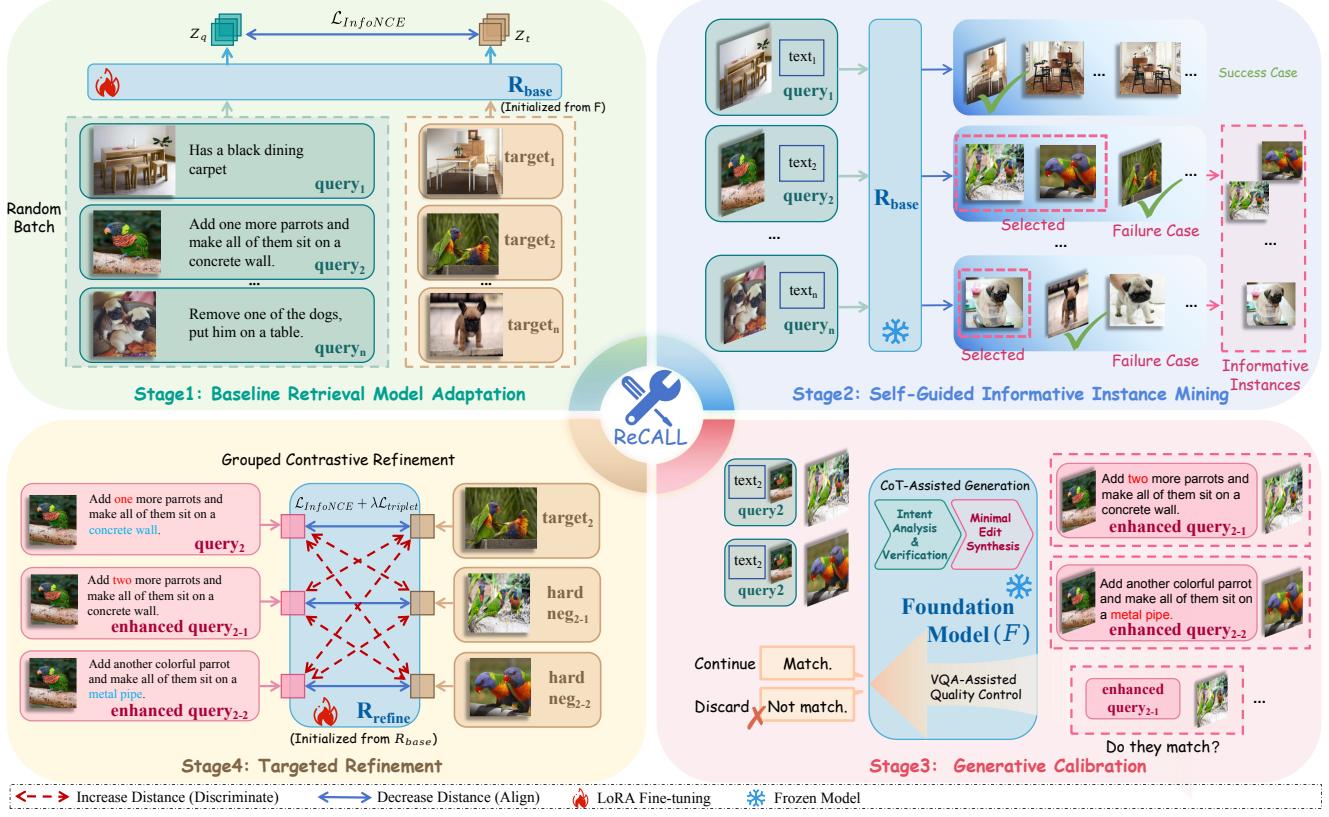


Figure 2. Overview of the **RecALL** framework. (1) **Stage 1:** A baseline retriever \mathcal{R}_{base} is adapted from the foundation model \mathcal{F} via standard fine-tuning. (2) **Stage 2 (Diagnose):** \mathcal{R}_{base} surfaces its own failure cases via self-guided informative instance mining. (3) **Stage 3 (Generate):** Leveraging native reasoning (CoT), \mathcal{F} synthesizes minimally edited corrective instructions for the mined informative instances. (4) **Stage 4 (Refine):** Based on the original and enhanced triplets, a Grouped Contrastive Refinement strategy is employed to produce the final \mathcal{R}_{refine} , effectively recalibrating the degraded capabilities.

ancy between I_t and I_h , so that the new triple (I_r, \tilde{T}_m, I_h) conveys the informative supervision to further unlock the fine-grained discriminative powers of the retriever. Concretely, we employ a multi-step reasoning procedure with \mathcal{F} to identify the semantic mismatch between the query (I_r, T_m) and I_h , and then applies the necessary minimal textual changes, consisting of the following two steps:

1. **Intent Decomposition & Verification:** \mathcal{F} decomposes T_m into atomic intents and verifies each against (I_r, I_h) , determining which intents are violated in I_h .
2. **Minimal Edit Synthesis:** \mathcal{F} retains the common intents (I_r, I_h) and regenerates only the violated components, producing the corrected instruction \tilde{T}_m .

This procedure induces the corrective triplet (I_r, \tilde{T}_m, I_h) , which provides dense and fine-grained supervision: the minimal textual edits from T_m to \tilde{T}_m directly mirror the subtle visual differences between I_t and I_h , encouraging the retriever to learn from these challenging and informative distinctions explicitly.

VQA-Assisted Quality Control. To ensure reliability, we

further apply a semantic consistency check strategy with the discriminative understanding ability of \mathcal{F} . Specifically, we prompt \mathcal{F} with targeted VQA questions about key attributes in \tilde{T}_m . Only triplets that receive high-confidence and internally consistent answers are retained for the final refinement stage.

3.5. Stage 4: Targeted Refinement

The final stage performs targeted refinement of \mathcal{R}_{base} guided by the corrective supervision generated in Sec. 3.4. We initialize \mathcal{R}_{refine} from \mathcal{R}_{base} and train it to internalize the fine-grained distinctions revealed by the newly constructed triplets, which is accomplished through two key components: grouped contrastive refinement and a dual optimization objective.

3.5.1. Grouped Contrastive Refinement

To fully exploit the corrective supervision from Sec. 3.4 for continual learning, we adopt a structured batching strategy. For each query, we build a *micro-group* containing both the original positive triplet (I_r, T_m, I_t) and its corrective coun-

terpart (I_r, \tilde{T}_m, I_h) . This grouping exposes the model’s blind spots within a single gradient update. By placing I_t together with its corresponding hard negative I_h , as well as the minimally different instructions T_m and \tilde{T}_m in the same batch, the model is encouraged to discriminate between visually adjacent samples via fine-grained semantic cues. As a result, the mined hard negatives serve as effective anchors for refining decision boundaries.

3.5.2. Dual Optimization Objective

To balance global retrieval performance and fine-grained correction, we optimize \mathcal{R}_{refine} using a hybrid objective:

InfoNCE Loss ($\mathcal{L}_{infoNCE}$). We apply the standard InfoNCE loss [33] over the entire batch, preserving the global structure learned in Sec. 3.2 while accommodating new distinctions:

$$\mathcal{L}_{infoNCE} = -\log \frac{\exp(s(z_q, z_{t+})/\tau)}{\sum_{z_t \in \mathcal{B}} \exp(s(z_q, z_t)/\tau)}, \quad (1)$$

where \mathcal{B} denotes the batch of target representations, τ is the temperature parameter, and $s(u, v) = \frac{u^\top v}{\|u\|\|v\|}$ denotes the cosine similarity. Additionally, z_q is the query representation derived from the input (I_r, T_m) , z_{t+} is the representation of the positive ground-truth image I_t , and z_t is a generic target representation from the batch \mathcal{B} .

In-Group Triplet Margin Loss ($\mathcal{L}_{triplet}$). To explicitly enforce the separation between the target and the specific hard negative within each micro-group, we add a margin-based loss [37]:

$$\mathcal{L}_{triplet} = \max(0, s(z_q, z_{t-}) - s(z_q, z_{t+}) + m), \quad (2)$$

where m is a margin hyperparameter, and z_{t-} corresponds to the hard negative I_h identified in the diagnose stage.

Combining the above two losses, the final object is formulated as:

$$\mathcal{L}_{total} = \mathcal{L}_{infoNCE} + \lambda \mathcal{L}_{triplet}, \quad (3)$$

where λ balances global alignment and targeted refinement. This optimization strategy effectively counteracts capability degradation, re-incentivizing the model’s fine-grained compositional reasoning.

In summary, ReCALL implements a diagnose–generate–refine pipeline that surfaces the failure cases of the baseline retriever, generates precise corrective supervision with \mathcal{F} , and internalizes these distinctions through targeted refinement. This process counteracts capability degradation and restores the fine-grained compositional reasoning required for reliable CIR.

4. Experiments

4.1. Datasets and Evaluation Metrics

Datasets. Following prior work [24, 46, 56], we evaluate our method on two widely adopted composed image retrieval (CIR) benchmarks, including Fashion IQ and CIRR.

FashionIQ [55] is a fine-grained benchmark dataset focusing on the fashion domain. It consists of triplets sourced from e-commerce websites, where each triplet comprises a reference image, a target image, and a natural language instruction describing the desired modifications. The dataset is divided into three categories: Dress, Shirt, and Toptee, making it particularly suitable for assessing the ability of models to understand subtle attribute changes such as color, pattern, and style.

CIRR [29] serves as a testbed for generalization in open-domain scenarios. It is derived from the real-world NLVR2 [40] dataset, with triplets involving complex object interactions and relational changes. In contrast to the domain-specific nature of FashionIQ, it offers a complementary and challenging evaluation scenario.

Evaluation Metrics. Following standard protocol [9, 41, 42], we adopt *Recall@K* ($R@K$) as our primary metric, which measures the percentage of queries where the ground-truth target appears in the top- K results. For FashionIQ, we report $R@10$ and $R@50$ averaged across its three categories. For CIRR, we report $R@1$, $R@5$, $R@10$, and $R@50$. Additionally, for CIRR, we leverage its unique design to report *Recall_{subset}@K* ($R_{subset}@K$) with K in $\{1, 2, 3\}$. This subset metric measures the ability to retrieve the correct item from a challenging, curated subset of six candidates, offering a more targeted measure of discriminative power.

4.2. Implementation Details

We use Qwen2.5-VL-7B [3] as the backbone of ReCALL and fine-tune it with LoRA [18] (rank $r=16$) on 8 NVIDIA H20 GPUs. Unless otherwise specified, we share the same training configuration across all stages. For FashionIQ, we use a learning rate of 4×10^{-5} , InfoNCE temperature $\tau=0.03$ and a global batch size of 512, running 200 optimization steps for Stage 1 and 250 steps for Stage 4. For CIRR, we adopt a learning rate of 2×10^{-5} , $\tau=0.02$ and the same batch size, with 300 and 350 steps in Stage 1 and Stage 2 respectively. The triplet loss margin is set to $m=0.05$, and the weight λ is 0.30 on FashionIQ and 0.25 on CIRR.

4.3. Comparison with State-of-the-Art Methods

We compare our proposed ReCALL framework against existing state-of-the-art methods on both CIRR and Fash-

Table 1. Performance comparison on the CIRR test set. We compare the proposed **ReCALL** ($\mathcal{R}_{\text{refine}}$) against state-of-the-art methods. $\mathcal{R}_{\text{base}}$ denotes the baseline retriever obtained after **Stage 1**, which serves as the starting point for our refinement pipeline. The "Avg." metric is computed as $(R@5 + R_{\text{subset}}@1)/2$. Best results are in **bold**, and the second-best are underlined. The bottom row (Δ) highlights the *relative improvement* of ReCALL over $\mathcal{R}_{\text{base}}$, quantifying the efficacy of our recalibration strategy.

Method	Venue	Recall@ k				Recall _{subset} @ k			Avg.
		k=1	k=5	k=10	k=50	k=1	k=2	k=3	
TIRG [48]	CVPR'19	14.61	48.37	64.08	90.03	-	-	-	-
ARTEMIS [12]	ICLR'22	16.96	46.10	61.31	87.73	39.99	62.20	75.67	43.05
TG-CIR [53]	MM'23	45.25	78.29	87.16	97.30	72.84	89.25	95.13	75.57
SPRC [4]	ICLR'24	51.96	82.12	89.74	97.69	80.65	92.31	96.60	81.39
LIMN [52]	TPAMI'24	43.64	75.37	85.42	97.04	69.01	86.22	94.19	72.19
CoVR-2 [47]	TPAMI'24	50.43	81.08	88.89	98.05	76.75	90.34	95.78	79.28
CaLa [19]	SIGIR'24	49.11	81.21	89.59	98.00	76.27	91.04	96.46	78.74
ENCODER [25]	AAAI'25	46.10	77.98	87.16	97.64	76.92	90.41	95.95	77.45
CIR-LVLM [43]	AAAI'25	53.64	83.76	90.60	97.93	79.12	92.33	96.67	81.44
QuRe [21]	ICML'25	52.22	82.53	90.31	98.17	78.51	91.28	96.48	80.52
CCIN [46]	CVPR'25	53.41	<u>84.05</u>	<u>91.17</u>	98.00	-	-	-	-
TME [24]	CVPR'25	53.42	82.99	90.24	98.15	<u>81.04</u>	<u>92.58</u>	<u>96.94</u>	<u>82.01</u>
Baseline($\mathcal{R}_{\text{base}}$)	-	51.23	82.15	90.20	<u>98.20</u>	77.57	91.83	96.34	79.86
ReCALL ($\mathcal{R}_{\text{refine}}$)	-	55.52	84.07	91.83	98.55	81.49	93.35	97.64	82.81
<i>Improvement</i> (Δ)		+8.38%	+2.34%	+1.81%	+0.36%	+5.06%	+1.65%	+1.35%	+3.70%

FashionIQ benchmarks, covering both traditional dual-tower approaches and recent MLLM-based retrievers.

Results on CIRR. Table 1 reports the quantitative results on the CIRR test set. The baseline ($\mathcal{R}_{\text{base}}$) alone delivers a competitive 51.23% on R@1, confirming the inherent potential of MLLM architectures for compositional reasoning. Building on this, ReCALL establishes a new state-of-the-art of **55.52%**, outperforming the concurrent MLLM-based CIR-LVLM [42] (53.64%). Notably, this **8.38%** on R@1 relative improvement over $\mathcal{R}_{\text{base}}$ compellingly validates the effectiveness of our *diagnose–generate–refine* pipeline in rectifying capability degradation. Furthermore, on the Recall_{subset} metrics designed for hard-negative evaluation, ReCALL secures a leading R_{subset}@1 of **81.49%**. These gains confirm that our synthesized triplets successfully sharpen the model’s decision boundaries against highly confounding visual distractors.

Results on FashionIQ. Table 2 details the quantitative results on the FashionIQ validation set. Despite inherent challenges such as high label noise and subtle attribute manipulations, ReCALL demonstrates consistent superiority by achieving the highest average **R@10 of 57.04%** and **R@50 of 76.42%**, successfully outperforming the concurrent CIR-LVLM [42]. When compared to our $\mathcal{R}_{\text{base}}$, ReCALL delivers a robust **7.16%** relative improvement in average R@10, with gains reaching as high as **10.71%** in the *Dresses* category. These pervasive improvements across all categories compellingly validate that our Minimal Corrective Editing strategy effectively captures nuanced visual-semantic distinctions, enabling precise retrieval even when target images

differ from references by only fine-grained details.

4.4. Ablation Studies

We conduct a series of experiments to validate the efficacy, efficiency, and generalization capabilities of the ReCALL.

Diagnose Phase: Impact of Self-Guided Informative Instance Mining. We further investigate the necessity of the Diagnose phase. A prevailing trend in recent MLLM adaptation involves indiscriminate large-scale data synthesis. To strictly simulate this scaling approach, we establish a *Random Mining* baseline. Specifically, for every training query, we first retrieve the top-50 candidate images using the frozen $\mathcal{R}_{\text{base}}$. From this candidate pool, we randomly sample negative instances to undergo the generation pipeline, strictly maintaining the same data scale as our method. To guarantee experimental robustness, we report the mean and standard deviation across four independent runs (using different random seeds) in Table 3. The results reveal a critical inefficiency in the blind synthesis paradigm. Even when averaged over multiple runs, Random Mining yields only marginal gains (improving R@10 from 53.23% to 53.80%), whereas our Self-Guided strategy delivers a substantial boost to 57.04%. This remarkable contrast demonstrates that indiscriminate synthesis often results in effective redundancy: since the candidates are drawn randomly from the top-50, many have been likely already correctly ranked by the model, thus providing negligible gradient signals. In contrast, ReCALL follows a *diagnose-then-generate* philosophy, precisely concentrating the generative budget on the model’s active failure cases. By ensuring that every synthesized triplet targets a specific cognitive defi-

Table 2. Performance comparison on the FashionIQ validation set. We compare the proposed **ReCALL** ($\mathcal{R}_{\text{refine}}$) against state-of-the-art methods in terms of Recall@ k (%). Consistent with Table 1, $\mathcal{R}_{\text{base}}$ denotes the baseline retriever obtained after **Stage 1**, serving as the starting point for recalibration. Best results are in **bold**, and the second-best are underlined. The bottom row (Δ) highlights the *relative improvement* of ReCALL over $\mathcal{R}_{\text{base}}$.

Method	Venue	Dresses		Shirts		Tops&Tees		Avg.	
		R@10	R@50	R@10	R@50	R@10	R@50	R@10	R@50
TIRG [48]	CVPR'19	14.13	34.61	13.10	30.91	14.79	34.37	14.01	33.30
ARTEMIS [12]	ICLR'22	25.68	51.05	21.57	44.13	28.59	55.06	25.28	50.08
FashionSAP [16]	CVPR'23	33.71	60.43	41.91	70.93	33.17	61.33	36.26	64.23
FAME-ViL [15]	CVPR'23	42.19	67.38	47.64	68.79	50.69	73.07	46.84	69.75
SyncMask [39]	CVPR'24	33.76	61.23	35.82	62.12	44.82	72.06	38.13	65.14
SADN [51]	MM'24	40.01	65.10	43.67	66.05	48.04	70.93	43.91	67.36
CaLa [19]	SIGIR'24	42.38	66.08	46.76	68.16	50.93	73.42	46.69	69.22
CoVR-2 [47]	TPAMI'24	46.53	69.60	51.23	70.64	52.14	73.27	49.96	71.17
SPRC [4]	ICLR'24	49.18	72.43	55.64	73.89	59.35	78.58	54.72	74.97
CIR-LVLM [43]	AAAI'25	<u>50.42</u>	73.60	58.59	<u>75.86</u>	<u>59.61</u>	<u>78.99</u>	<u>56.21</u>	<u>76.14</u>
CCIN [46]	CVPR'25	49.38	72.58	55.93	74.14	57.93	77.56	54.41	74.76
TME [24]	CVPR'25	49.73	71.69	56.43	74.44	59.31	78.94	55.15	75.02
QuRe [21]	ICML'25	46.80	69.81	53.53	72.87	57.47	77.77	52.60	73.48
Baseline($\mathcal{R}_{\text{base}}$)	-	46.80	70.60	55.00	74.39	57.88	78.12	53.23	74.37
ReCALL ($\mathcal{R}_{\text{refine}}$)	-	51.81	<u>73.48</u>	<u>58.49</u>	76.59	60.83	79.19	57.04	76.42
<i>Improvement</i> (Δ)		+10.71%	+4.08%	+6.35%	+2.96%	+5.10%	+1.37%	+7.16%	+2.76%

Table 3. Ablation study on the mining strategy on the FashionIQ validation set. We compare our **Self-Guided Mining** against a **Random Mining** baseline under the same data budget. To ensure statistical robustness, results for the Random strategy are averaged over **four independent runs** with different random seeds.

Mining Strategy	R@10	R@50	Mean
$\mathcal{R}_{\text{base}}$	53.23	74.37	63.80
+ Random Mining	53.80 ± 0.20	74.32 ± 0.06	64.06 ± 0.10
+ Self-Guided	57.04	76.42	66.73

Table 4. Ablation study of the core components on the FashionIQ validation set. **CG**: CoT-assisted Generation, **VC**: VQA-Assisted Quality Control, **GR**: Grouped Contrastive Refinement. • denotes the component is included, and ○ denotes excluded. All metrics are the average over the three categories (in %). The stepwise performance improvements validate the effectiveness of each proposed module.

Baseline	Components			Metrics (Avg.)		
	CG	VC	GR	R@10	R@50	Mean
•	○	○	○	53.23	74.37	63.80
•	•	○	○	55.41	75.17	65.29
•	•	•	○	56.13	76.04	66.09
•	•	•	•	57.04	76.42	66.73

ciency, ReCALL achieves superior capability enhancement with maximal data efficiency.

Generate Phase: Effectiveness of Generative Calibration (CG & VC). This set of experiments verifies the core

Generate phase using a progressive study detailed in Table 4 (Rows 1-3). We leverage the foundation model \mathcal{F} to create corrective supervision. The introduction of CoT-assisted Generation (CG) yields a substantial gain, boosting R@10 from 53.23% to 55.41%. This absolute improvement of 2.18% confirms that capitalizing on native generative reasoning of \mathcal{F} to synthesize targeted supervision effectively mitigates cognitive deficits. Furthermore, adding VQA-Assisted Quality Control (VC) further elevates R@10 to 56.13%. This step utilizes intrinsic discriminative understanding of \mathcal{F} to filter out noise, ensuring that only high-quality triplets guide the training. In all, these results empirically demonstrate that our framework successfully internalizes the robust compositional reasoning abilities of the foundation model, alleviating capability degradation caused by the initial adaptation.

Refine Phase: Necessity of Grouped Refinement (GR). We finally validate the *Refine* phase (Table 4, Rows 3-4), which focuses on how to effectively internalize the corrective supervision. As shown in Row 3, merely expanding the training set with synthetic triplets via standard random batching offers limited gains. By contrast, enabling Grouped Contrastive Refinement (GR) achieves the peak performance of 57.04% in R@10. This comparison highlights the importance of optimal data utilization: our grouped strategy is specifically designed to leverage the subtle visual and textual contrasts created in the generation phase. By forcing a direct, in-batch comparison between the target and its synthesized near-neighbor, this mechanism compels the model to explicitly resolve ambiguities

within the micro-group. This optimal signal transmission effectively translates the corrective supervision into sharper, fine-grained discriminative boundaries, successfully recalibrating the degraded compositional reasoning capability.

Generalizability across Backbones. To verify that ReCALL is a model-agnostic framework rather than a specific patch for weaker architectures, we applied our method to a more advanced foundation model, **Qwen3-VL-8B**. As illustrated in Fig. 4, the baseline adaptation (\mathcal{R}_{base}) of Qwen3-VL-8B already exhibits a strong starting point, significantly outperforming the standard Qwen2.5-VL-7B baseline (e.g., 55.93% vs. 51.23% R@1 on CIRR). Despite this high baseline, applying ReCALL still yields consistent improvements, boosting CIRR R@1 to 57.09% and FashionIQ R@10 to 57.60%. It is worth noting that even as the foundation model becomes stronger, the *Capability Degradation* phenomenon stemming from the paradigm conflict between generation and retrieval persists. Our results confirm that ReCALL effectively addresses this fundamental issue, demonstrating scalability and robustness across different model capacities.

4.5. Qualitative Analysis

To visually evidence *Capability Degradation* and the effectiveness of our subsequent recalibration, Fig. 3 presents two representative challenging cases from the FashionIQ and CIRR datasets that demand precise fine-grained reasoning. Crucially, we verify that the Foundation Model (\mathcal{F}) correctly identifies both targets via VQA reasoning, confirming that the requisite compositional knowledge has already existed in the pre-trained model. However, the adapted \mathcal{R}_{base} fails in both instances, exposing a clear degradation pattern. The baseline retains coarse-grained understanding, such as identifying a “blue dress” or a “wolf on snow,” but collapses on specific constraints. For example, it retrieves a sleeveless dress instead of the requested “half sleeved” one, and a profile-view wolf ignoring the instruction “facing the camera.” In contrast, ReCALL successfully rectifies these errors. By explicitly diagnosing these blind spots and re-aligning the representation space with the native reasoning ability of the foundation model, our method restores the lost sensitivity to subtle attributes and spatial relations, accurately retrieving the correct targets in both scenarios.

5. Conclusion

In this work, we address Capability Degradation—a critical deterioration of fine-grained compositional reasoning when adapting generative MLLMs for discriminative retrieval—by proposing the ReCALL framework, which utilizes the intrinsic zero-shot reasoning of MLLM via a unique diagnose-generate-refine pipeline to actively create and internalize targeted corrective supervision. Specifically,

our method employs self-guided informative instance mining and grouped refinement to successfully embed the foundation model’s reasoning into the retrieval space. Empirical results substantiate ReCALL’s effectiveness, achieving state-of-the-art (SOTA) performance on mainstream CIR benchmarks like CIRR and FashionIQ, thereby paving the way for reliable and fine-grained MLLM-based retrieval.

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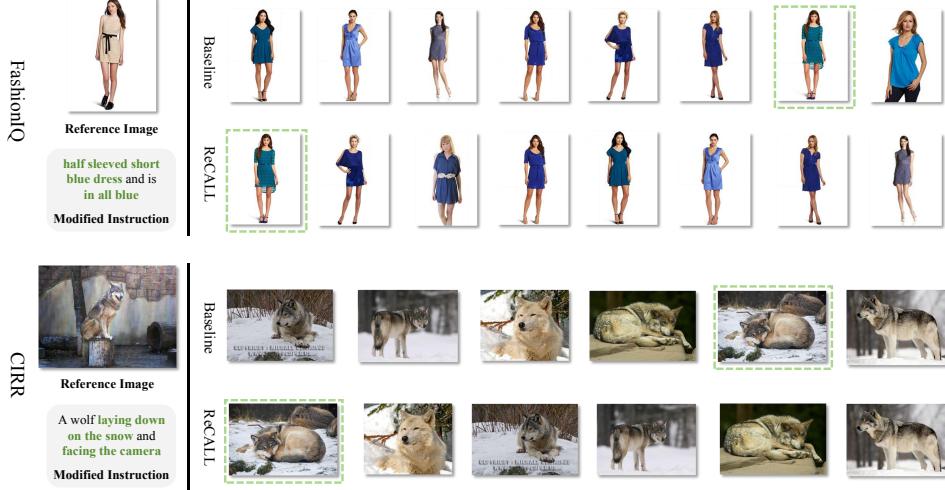


Figure 3. Qualitative comparison between the baseline ($\mathcal{R}_{\text{base}}$) and our ReCALL ($\mathcal{R}_{\text{refine}}$) on FashionIQ (top) and CIRR (bottom). The green dashed boxes indicate the ground-truth targets. $\mathcal{R}_{\text{base}}$ suffers from capability degradation, failing to capture specific details like “half sleeved” or “facing the camera,” while ReCALL successfully retrieves the correct targets by recalibrating these fine-grained reasoning.

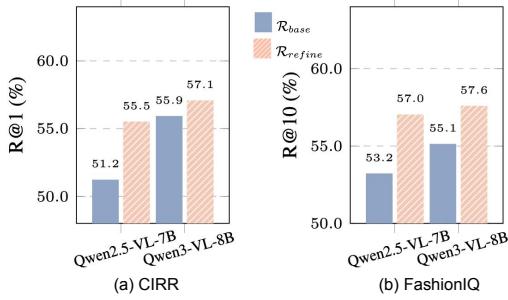


Figure 4. **Generalizability across backbones.** We validate ReCALL on stronger foundation models (**Qwen2.5-VL-7B** and **Qwen3-VL-8B**). Despite higher baselines, ReCALL consistently delivers performance gains on both (a) CIRR and (b) FashionIQ, confirming the strong generalization of our framework.

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