

VICO: Visual Environments Co-Evolving for Vision-Language Model Reasoning

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Abstract

Reinforcement learning with verifiable rewards (RLVR) has become a standard recipe for post-training vision-language models (VLMs), but it typically assumes a static training environment. As the actor improves, fixed tasks drift out of its learning frontier: many become trivial, others remain unsolvable; and the learning signal collapses. We argue that *VLM post-training should evolve the visual environment alongside the actor*, not just the actor itself. We propose VICO, a co-evolutionary framework in which an *actor* and an *Environment-as-Rewriter* (EnvRewriter) are trained jointly: the EnvRewriter edits verifiable image-side structures, such as scene graphs, chart tables, or protected region masks, and re-renders them to produce label-valid training samples whose difficulty is calibrated to the actor’s current ability through a pass-rate-based reward. This loop continuously re-aligns task difficulty with actor capability without any additional human annotation. Across nine multimodal benchmarks spanning mathematical reasoning and visually grounded understanding, VICO-8B improves over its base model by up to **+5.0%** on out-of-domain tasks, surpasses the strongest self-evolution and text-editing co-evolution baselines by **+4.3%** and **+8.4%** respectively, and stays comparable to chart-specialized RLVR methods using **16–160× fewer labeled samples**. By shifting from human-labeled supervision to image-editing co-evolution, VICO offers a scalable path beyond static-corpus RLVR for visual reasoning.

1 Introduction

Large Vision-Language Models (VLMs) have recently improved through reinforcement learning with verifiable rewards (RLVR) [14], where models learn from automatically checkable outcomes rather than dense human rationales [31]. This recipe has made self-evolution an attractive paradigm: rather than relying on costly human supervision, a model can generate tasks, collect rollouts, and improve from its own experience [22, 38]. Yet most self-evolution pipelines share a structural limitation: the actor

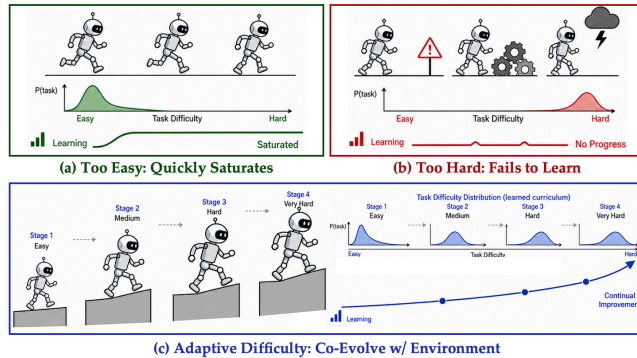


Figure 1: Co-evolution with adaptive visual environments and actors leads to better training.

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keeps changing, but the visual environment stays fixed. As the actor improves, fixed tasks drift out of its learning frontier, where many become trivial while others remain unsolvable. In both regimes, the rollout group provides little useful contrast (Figure 1): the empirical pass rate $\hat{p}$ moves toward 1 or 0, the Group Relative Policy Optimization (GRPO) reward variance, proportional to $\hat{p}(1 - \hat{p})$, collapses, and the learning signal weakens precisely when the actor is ready to learn more [15]. Crucially, $\hat{p}$ already tells us exactly how difficult each task is for the current actor, yet existing methods use it only for normalization or filtering, discarding a signal that could otherwise guide the environment itself. This raises the central question of our work: *can the visual environment adapt to the actor using the same rollout feedback that trains the actor?*

Answering this question (*i.e.*, adapting the visual environment), however, requires more than simply generating new images. Useful training samples must satisfy two constraints simultaneously. First, they should be *verifiable*: edits should not introduce ambiguous questions or incorrect labels, otherwise the verifiable reward signal that underpins RLVR breaks down. Second, they should be *capability-aligned*: edits should move tasks toward the actor’s current learning frontier rather than making them arbitrarily harder or easier. Human annotation [26, 25] satisfies both but does not scale, while offline augmentation with stronger teachers [6, 24] reduces annotation cost but produces a static distribution that cannot track the actor’s evolving weaknesses. What is missing is an automatic visual environment that adapts to the actor while preserving the validity of the label.

We propose VICO, a co-evolution framework that addresses both requirements through joint training of two VLMs. The *actor* learns to answer visual reasoning questions, while the *EnvRewriter* learns to perform verifiable structured edits to match the actor’s current ability. For each rewritten task, we sample a group of actor rollouts and reuse the resulting pass rate $\hat{p}$ as a shared learning signal: binary rollout rewards update the actor through GRPO, while $\hat{p}$ updates the EnvRewriter through an α -curriculum reward that peaks near $\hat{p} = 0.5$, steering edits into the actor’s *learnable zone*. We then evaluate VICO across three representative visual reasoning domains, including compositional reasoning, chart understanding, and general visual question answering, and against three categories of baselines: text-only rewriting, static-environment self-evolution, and offline augmentation with stronger teachers, including GPT-5 [29] and Nano Banana [12]. Across eight out-of-distribution benchmarks, VICO exceeds the strongest self-evolution baseline by +4.3% on average. Notably, even when stronger image generators are scaled up, static baselines plateau, indicating that the gains stem from the iterative actor–environment loop rather than from data generation quality alone. Our contributions are as follows:

- **An actor–environment co-evolution paradigm for VLM reasoning.** We introduce a framework in which the visual environment evolves alongside the actor, using the rollout pass rate $\hat{p}$ as a shared learning signal. This continually realigns task difficulty with actor capability and overcomes the saturation that limits fixed-environment self-evolution.
- **A verifiable image-editing training framework.** We design a pipeline that couples structured visual editing with RLVR, converting edited images into valid training samples through deterministic rendering and programmatic relabeling, with no human annotation.
- **Strong empirical performance across diverse benchmarks.** Across nine multimodal benchmarks, VICO surpasses RLVR baselines by +15.5% on average, exceeds the strongest self-evolution baseline by +4.3% on out-of-domain tasks, and outperforms the proprietary Gemini-2.5-Pro by +2.5%.
- **Annotation-efficient training.** VICO is competitive with chart-specialized RLVR methods using $16\times$ – $160\times$ fewer labeled samples, demonstrating that adaptive environments can substitute for large-scale human or teacher-model annotation.

2 Related Work

Reinforcement Learning for Vision-Language Reasoning. RLVR has become a standard post-training recipe for language and vision-language models, replacing dense human rationales with rule- or program-checkable outcomes [21, 31]. Recent multimodal extensions of RLVR target multi-step visual reasoning through cross-modal symbolic formalization [45], scaled rule-based reward training [27], and combined SFT-RL pipelines [10]. Subsequent work refines RLVR through efficient visual processing [44], weakness-driven problem generation [23], curiosity-driven exploration [9],

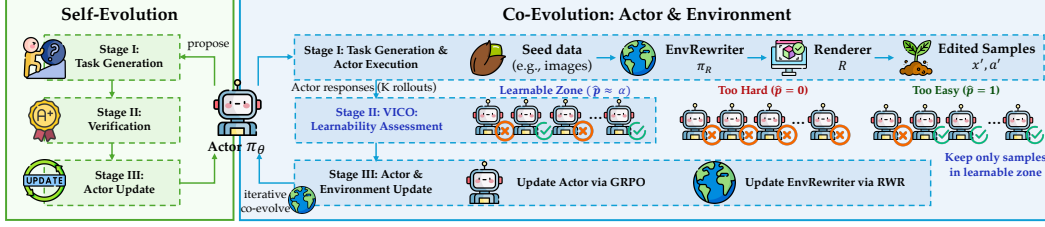


Figure 2: **VICO turns self-evolution into an adaptive actor–environment loop.** The EnvRewriter creates visual tasks, the Actor solves them, and shared rollouts update both policies: task rewards train the Actor, while difficulty-aligned rewards train the EnvRewriter.

and multi-turn world-model reasoning [37]. While these methods differ in reward design, exploration strategy, and training schedule, they share a common assumption: a fixed pool of visual tasks. *VICO instead treats the visual environment as a learnable component that co-adapts with the actor*, aiming to unlock new capabilities rather than refine existing ones over a static distribution [48].

Self-Evolving VLMs. Self-evolving VLMs reduce reliance on human-curated supervision by letting models generate, solve, or refine their own training data. MM-Zero bootstraps multimodal reasoning from zero labeled data by proposing and solving visual problems [22], VisPlay self-generates question-answer pairs from raw images for RL training [17], and Vision-Zero frames self-improvement as visual self-play with verifiable outcomes [38]. Related efforts apply self-evolution to visual games [43, 34], perception [50], image-quality assessment [40], self-refinement [11], and OCR hallucination mitigation [18]. Across these methods, the actor evolves but the visual environment remains fixed, leaving the training distribution increasingly misaligned with the actor’s current ability.

Co-Evolving VLMs and Environments. A more recent line of co-evolution work allows the environment to change with the model: GenEnv trains an environment policy for difficulty-aligned planning tasks [15], V-Zero perturbs the textual side of visual tasks while keeping the image pool fixed [35], C2-Evo co-evolves multimodal data and model training through model-driven generation [8], and Active-Zero retrieves from a large external image pool in an offline augmentation setting [16]. VICO differs from this line in two ways: it edits the visual substructure of each image rather than perturbing text or retrieving from a fixed pool, directly adapting the modality where reasoning is grounded; and it uses the actor’s own pass rate as the supervision for environment updates, providing a difficulty-calibration loop tightly coupled to the actor’s learning trajectory.

3 Methodology

VICO views visual reasoning training as an *actor–environment curriculum process* rather than a single model self-optimization problem. We maintain two policies: an *actor* π_a (the vision-language model being trained) and an *EnvRewriter* π_R (the environment that produces training samples). Unlike standard RLVR with a fixed training source, VICO enables both to co-evolve: π_a learns to solve visual reasoning tasks whose difficulty is shaped by the current EnvRewriter, while π_R is rewarded for producing edited images whose difficulty is aligned with the actor’s current capability — targeting the “learnable zone” where the learning signal is most effective.

3.1 Data-Evolving Paradigm: From Static RLVR to Adaptive Co-evolution

Standard RLVR minimizes a loss $\mathcal{L}(\theta)$ over a static dataset $\mathcal{D}_{\text{static}} = \{(x, q, a)\}$, where θ denotes the parameters of the actor. In contrast, VICO implements a *Data-Evolving Paradigm*. At each round t , the training dataset $\mathcal{D}_t$ is generated dynamically by the EnvRewriter π_R , based on the actor’s current pass rate. This establishes a feedback loop (Figure 2) in which the EnvRewriter’s goal is not to beat the actor, but to identify its “breaking points” and convert them into a training signal.

Table 1: **VICO keeps edited samples verifiable across domains.** Structured domains use deterministic recomputation, while natural images use constrained answer preservation; neither needs judging or relabeling.

Domain	Editing Interface	Label-Validity Rule
CLEVR [19]	Edit the scene graph: attributes, objects, shapes, or relations.	Re-execute the question program on the edited graph; reject rendering or ambiguity failures.
ChartQA [26]	Edit the CSV table under a two-tier rule: Tier 1 has a unique answer cell; Tier 2 has no unique cell mapping.	Tier 1 computes $a' = \text{table}'[r, c]$; Tier 2 preserves $a' = a$. Reject schema, rendering, or invariance failures.
ZwZ [39]	Edit only the complement of protected target masks, e.g., background or non-target distractors.	Preserve $(q', a') = (q, a)$; reject edits whose mask overlaps protected targets or fails rendering.

3.2 Seed Visual Data and Verifiable Sample Generation

We start VICO from a small seed visual dataset and let the EnvRewriter derive additional training examples by editing the structured or protected representation of each seed sample in subsequent rounds. The key requirement is that every edited sample remains *label-valid* while its difficulty changes. We therefore avoid unconstrained pixel-level generation. Instead, the answer can either be recomputed programmatically from the edited structure or preserved by construction through constrained editing. Table 1 summarizes the editing interface for each domain.

We experiment with three types of data: 2,000 CLEVR with scene graphs and question programs, 2,000 ChartQA with their underlying CSV tables, and 1,000 ZwZ with answer-relevant region annotations. The actor–environment co-evolution loop is shared across all three domains; only the verifiable editing interface depends on the structure available in each dataset. More details are provided in Appendix C. We further analyze seed-sampling stability in Appendix H.5; three ChartQA runs with different seed samples fluctuate by less than 2%.

3.3 Rewards and Co-Evolutionary Optimization

Actor Reward and Update. The EnvRewriter generates a training instance (x', q', a') with a verified answer a' , where a' is programmatically computed from the modified structured representation (Appendix C). This verifiable answer enables rule-based rewards, avoiding neural reward models that are prone to reward hacking. The actor’s response receives a reward +1 if it both produces the correct answer (exact match against a') and follows the required `<think>/<answer>` format; otherwise, it receives −1 (Appendix B.4) [52]. The actor π_a is updated to maximize this reward via GRPO [31] on edited triples sampled from $\mathcal{D}_a$.

EnvRewriter Reward and Update. The core innovation for π_R is a difficulty-calibration reward that targets a success-rate band around $\alpha = 0.5$. For each edited image x' , the actor generates K rollouts, and we compute the empirical pass rate $\hat{p}_{\text{final}}$ as the fraction of correct rollouts. The EnvRewriter reward is a bell-shaped function of $\hat{p}_{\text{final}}$ peaked at α (Appendix B.4), which discourages edits that are already mastered ($\hat{p}_{\text{final}} \rightarrow 1$) or hopeless ($\hat{p}_{\text{final}} \rightarrow 0$). We additionally apply a difficulty filter that excludes edits with $|\hat{p}_{\text{final}} - \alpha| > k_{\text{min}}$ from EnvRewriter updates, where $k_{\text{min}} \in (0, \frac{1}{2})$ is the maximum allowed deviation from α , to prevent overfitting to transient spikes; a theoretical justification is provided in Section 4. The EnvRewriter π_R is updated via Reward-Weighted Regression (RWR) on a weighted SFT set of edit trajectories, with stability ensured by a KL penalty to the initial EnvRewriter $\pi_R^{(0)}$ and a maximum KL threshold δ_{max} . Appendix B.1 Algorithm 1 summarizes the full optimization loop.

4 Theoretical Analysis of Difficulty-Calibrated VICO

We provide a simple analysis to clarify two properties of VICO’s co-evolution mechanism. First, edits with pass rates close to $\alpha = 0.5$ provide the strongest learning signal for the actor. Second, as the actor matures, the optimal target can shift away from 0.5, which explains the saturation observed in our experiments. Full derivations are deferred to Appendix E.

Intermediate difficulty maximizes the actor’s learning signal. Consider a stylized bandit setting where the actor receives a binary reward $r \in \{0, 1\}$ with success probability p on an edited image x' . Under a REINFORCE-style update [41] with a variance-minimizing baseline [20], and under a standard bounded-score assumption for policy-gradient updates, the squared gradient norm satisfies

$$\mathbb{E}[\|g(x', r)\|^2] \propto p(1 - p), \quad (4.1)$$

up to constants independent of p . Since $p(1 - p)$ is concave and maximized at $p = 1/2$, the gradient signal is strongest for edits of intermediate difficulty. Equivalently, maximizing $p(1 - p)$ is the same as minimizing $(p - \frac{1}{2})^2$. This supports adopting the α -Curriculum reward [15] $R_{\text{rewriter}}(\hat{p}) = \exp(-\beta(\hat{p} - \alpha)^2)$ with $\alpha = 0.5$ as the difficulty-calibration objective for the EnvRewriter.

A drift-corrected target predicts saturation. The target $\alpha = 0.5$ is optimal only when edits are costless. As the actor improves, its pass rate $\hat{p}_{\text{orig},t}$ on the unedited image rises. Forcing the edited sample back to $\hat{p} = 0.5$ may then require increasingly aggressive edits. These edits can move the training distribution away from the natural image manifold [1]. We model this trade-off by adding a quadratic drift penalty:

$$\Delta \text{Acc}_t = C_t p(1 - p) - \lambda \kappa_t (p - \hat{p}_{\text{orig},t})^2, \quad (4.2)$$

where $C_t > 0$ denotes the actor’s remaining learning headroom, and $\lambda \kappa_t \geq 0$ controls the drift cost. Maximizing this concave objective gives

$$p_t^* = \frac{1}{2} + \rho_t (\hat{p}_{\text{orig},t} - \frac{1}{2}), \quad \rho_t = \frac{\lambda \kappa_t}{C_t + \lambda \kappa_t} \in [0, 1], \quad (4.3)$$

so the optimal target is a convex combination of 0.5 and $\hat{p}_{\text{orig},t}$. When the actor has large headroom ($\rho_t \rightarrow 0$), the optimal target remains near 0.5. As headroom shrinks or drift cost increases ($\rho_t \rightarrow 1$), the optimum moves toward the unedited pass rate. Continued editing then enters a drift-dominated regime, where stronger perturbations bring smaller gains and may eventually hurt performance. This analysis predicts diminishing per-round gains, fewer sweet-zone samples, and eventual saturation, which we verify in Appendix E.6.

5 Experiments

5.1 Experimental Setups

Training Setup. For the Actor π_a , we train via GRPO [31] with $n = 8$ on-policy rollouts and a learning rate 1×10^{-6} . The EnvRewriter π_R is updated via reward-weighted LoRA SFT with $\beta = 4.0$ and $\alpha = 0.5$ ([15]). We use AdamW for both policies, run VICO for $T = 5$ rounds, and use up to $8 \times$ A100-80GB GPUs with verl [32]. We train Qwen3-VL-8B [2] on three visual datasets, and Qwen2.5-VL-7B [3] and InternVL3-8B [53] on chart understanding to assess backbone generalizability. We validate VICO on three visual reasoning domains: CLEVR [19] for compositional reasoning, ChartQA [26] for chart reasoning, and ZwZ [39] for natural-image VQA. Full hyperparameters, two-stage training, dataset examples, and multi-seed analyses are in Appendix B.

Tasks and Datasets. We evaluate on nine benchmarks under identical zero-shot settings (temperature 0.7, top- p 1.0, max response length 3,824 tokens). For mathematical reasoning, we use MathVista [25], MathVision [36], MathVerse [51], WeMath [30], and LogicVista [42]. For chart reasoning, we use ChartQA [26]. For general vision-centric understanding, we use MMMU [47], MMVP [49], and BLINK [13]. The *Average* column in Table 2 is the equally weighted average of the mathematical-reasoning average and the vision-centric average.

Baselines. We compare VICO against three categories of strong baselines reflecting different post-training paradigms: (1) **RLVR-trained reasoning models** trained with RLVR on human-labeled data—R1-OneVision-7B [45], MM-Eureka-Qwen-7B [27], OpenVLThinker-7B [10]; (2) **Self-evolution models** that evolve the model in a fixed environment—MM-Zero-8B [22], three VisionZero-7B variants (CLEVR, Chart, Real-world), and VisionZero-InternVL3-8B [38]; (3) **Co-evolution baseline** V-Zero [35], which perturbs question-answer pairs without editing the visual environment. These three categories isolate the effect of *visual-environment co-evolution* from data-rich RL post-training and model-side self-evolution. Implementation details are in Appendix B.

Table 2: **VICO achieves the strongest overall performance among comparable open-source VLMs.** We report accuracy on nine multimodal reasoning benchmarks; **bold** marks the best result and underline marks the second-best among non-commercial models.

Baselines ($\downarrow$)	Mathematical Reasoning							General Vision-Centric				All
Datasets ($\rightarrow$)	MathVista	MathVision	ChartQA	MathVerse	WeMath	LogicVista	avg.	MMMU	MMVP	BLINK	avg.	avg.
<i>Commercial VLMs (For reference)</i>												
GPT-4o	61.4	30.4	80.7	50.2	40.0	45.9	51.4	65.1	86.3	60.0	70.47	61.0
GPT-5	80.2	41.1	85.9	68.1	64.7	49.1	64.9	68.6	84.7	74.8	76.0	70.4
Gemini-2-Flash	73.4	41.3	77.0	54.4	57.1	56.2	56.9	52.6	83.0	59.6	65.1	62.5
Gemini-2.5-Pro	72.8	29.6	80.1	67.0	68.9	52.7	61.9	54.8	75.7	78.1	69.5	65.7
Gemini-3.1-pro	83.3	34.7	84.1	67.8	65.9	57.4	65.5	60.0	89.7	83.5	77.7	71.6
<i>Open-Source VLMs</i>												
Qwen2.5-VL-7B	68.2	25.6	76.4	39.6	60.7	47.2	53.0	54.7	76.8	55.2	62.2	57.6
Qwen3-VL-8B	67.7	31.5	76.9	50.6	72.0	55.1	59.0	55.8	77.7	68.9	67.5	63.2
InternVL3-8B	60.4	21.3	69.9	32.2	61.3	34.6	46.6	55.3	64.3	61.2	60.3	53.5
InternVL3-14B	74.1	33.8	<u>87.3</u>	44.2	68.9	51.6	60.0	56.4	76.30	60.2	64.3	62.2
<i>RL-Trained Reasoning Baselines</i>												
OpenVLThinker-7B	70.2	25.3	59.9	47.9	36.5	44.3	47.4	36.1	71.7	61.2	50.0	48.7
MM-Eureka-Qwen-7B	73.0	26.9	58.2	50.3	36.2	42.9	47.9	50.1	73.0	58.3	51.7	49.8
MM-Eureka-InternVL-8B	62.4	22.1	54.9	32.1	58.2	38.9	44.8	51.6	74.3	61.0	50.0	47.4
R1-OneVision-7B	64.1	24.1	73.4	46.4	61.8	44.5	52.4	46.4	61.3	48.7	52.3	52.3
<i>Self-evolution</i>												
MM-Zero (Qwen3-VL-8B)	67.7	39.6	80.8	45.1	73.4	55.4	60.3	58.7	77.3	67.5	67.8	64.1
VisionZero-Qwen2.5-VL-7B (CLEVR)	72.2	28.4	86.3	53.2	49.8	45.8	56.0	53.0	79.5	56.0	58.0	57.0
VisionZero-Qwen2.5-VL-7B (Chart)	72.4	28.9	87.2	52.5	51.2	43.5	56.0	53.6	79.1	56.8	58.1	57.0
VisionZero-Qwen2.5-VL-7B (RW)	73.1	28.5	86.3	52.1	50.8	42.6	55.6	52.5	79.2	57.2	57.8	56.7
VisionZero-InternVL3-8B	62.2	24.2	53.0	32.9	28.7	41.8	40.5	56.9	69.0	63.3	47.2	43.9
<i>Co-evolution</i>												
V-Zero (Qwen2.5-VL-7B)	69.6	27.0	-	42.6	-	48.6	47.0	58.6	-	66.9	62.8	54.9
VICO-Qwen3-VL-8B (CLEVR)	72.8	41.0	86.3	56.0	76.8	57.8	65.1	64.9	80.3	69.9	71.7	68.4
Direct GRPO	71.6 ± 1.2	37.8 ± 3.2	78.1 ± 8.2	54.0 ± 0.1	71.2 ± 0.6	54.7 ± 3.1	61.2 ± 3.9	64.1 ± 0.8	78.3 ± 2.0	66.1 ± 3.8	69.5 ± 2.2	65.4 ± 3.0
Supervised GRPO	69.4 ± 3.4	36.9 ± 4.1	78.6 ± 7.1	54.1 ± 1.9	72.5 ± 4.3	56.0 ± 1.8	61.2 ± 3.9	54.6 ± 10.3	76.3 ± 4.0	68.3 ± 1.6	66.4 ± 5.3	63.8 ± 4.6
VICO-Qwen3-VL-8B (Chart)	78.4	39.4	89.1	55.0	74.5	56.5	65.5	65.2	79.7	70.5	71.8	68.6
Direct GRPO	70.9 ± 7.5	37.9 ± 1.5	83.8 ± 5.3	52.7 ± 2.3	73.0 ± 1.5	57.0 ± 0.5	62.5 ± 3.0	65.0 ± 0.2	77.7 ± 2.0	65.8 ± 4.7	69.5 ± 3.3	66.0 ± 2.6
Supervised GRPO	75.6 ± 2.8	36.1 ± 3.3	79.4 ± 9.7	51.8 ± 3.2	70.1 ± 4.4	56.0 ± 0.5	61.5 ± 4.0	56.8 ± 8.4	76.7 ± 3.0	68.7 ± 1.8	67.4 ± 4.4	64.4 ± 4.2
VICO-Qwen3-VL-8B (Real VQA)	75.8	40.8	86.2	54.1	73.2	59.6	65.0	61.5	79.3	71.5	70.8	67.9
Direct GRPO	71.9 ± 3.9	37.1 ± 3.7	79.8 ± 6.4	51.0 ± 1.1	72.1 ± 1.1	58.3 ± 1.3	61.7 ± 3.3	53.7 ± 7.8	77.7 ± 1.6	57.2 ± 14.3	62.9 ± 7.9	62.3 ± 5.6
Supervised GRPO	70.6 ± 5.2	37.6 ± 3.2	77.0 ± 9.2	53.0 ± 1.1	71.2 ± 2.0	58.9± 0.7	61.4 ± 3.6	54.2 ± 7.3	76.3 ± 3.0	58.8 ± 12.7	63.1 ± 7.7	62.2 ± 5.7

Table 3: **VICO improves VLM backbones with far less training data.** The same pipeline improves Qwen2.5-VL-7B and InternVL3-8B, while using $16\times-160\times$ less data than chart-specialized RL models. Overall average uses the seven displayed benchmarks; **bold** marks the best result and underline marks the second-best. *Average is computed over reported columns only.

Baselines ($\downarrow$)	Seed Data	Mathematical Reasoning					Vision-Centric		Overall
Datasets ($\rightarrow$)		MathVista	MathVerse	ChartQA	WeMath	LogicVista	MMMU	BLINK	avg.
<i>Chart-Specialized Methods</i>									
Chart-R1-7B [7]	$\sim 33k$	-	-	91.0	-	-	-	-	-
Bespoke-MiniChart-7B [28]	$\sim 91k$	-	-	<u>89.5</u>	-	-	-	-	-
ECD (Qwen2.5-VL-7B) [46]	$\sim 320k$	-	-	85.3	-	-	-	-	-
<i>Qwen2.5-VL-7B Family</i>									
Qwen2.5-VL-7B (base)	-	68.2	39.6	76.4	60.7	47.2	54.7	55.2	57.4
OpenVLThinker-7B [10]	$\sim 50k$	70.2	47.9	59.9	36.5	44.3	36.1	61.2	50.9
MM-Eureka-Qwen-7B [27]	15k	<u>73.0</u>	50.3	58.2	36.2	42.9	50.1	<u>58.3</u>	52.7
R1-OneVision-7B [45]	10k	64.1	46.4	73.4	<u>61.8</u>	44.5	46.4	48.7	55.0
VisionZero-Qwen7B (CLEVR) [38]	2000	72.2	<u>53.2</u>	86.3	49.8	<u>45.8</u>	53.0	56.0	59.5
VisionZero-Qwen7B (Chart)	1000	72.4	52.5	<u>87.2</u>	51.2	43.5	53.6	56.8	<u>59.6</u>
VisionZero-Qwen7B (Real-world)	1000	73.1	52.1	86.3	50.8	42.6	52.5	57.2	59.2
C2-Evo [8]	-	50.2	19.1	-	-	-	-	-	34.7*
VICO-Qwen2.5-VL-7B (Chart)	2000	72.8	54.9	88.0	67.6	44.0	<u>53.8</u>	53.7	62.1
<i>InternVL3-8B Family</i>									
InternVL3-8B (base)	-	60.4	32.2	<u>69.9</u>	<u>61.3</u>	34.6	55.3	<u>61.2</u>	<u>53.6</u>
MM-Eureka-InternVL-8B	15k	<u>62.4</u>	32.1	54.9	58.2	38.9	51.6	61.0	51.3
VisionZero-InternVL3-8B	2000	62.2	<u>32.9</u>	53.0	28.7	41.8	56.9	63.3	48.4
VICO-InternVL3-8B (Chart)	2000	68.9	57.6	80.6	63.4	<u>40.2</u>	<u>55.7</u>	58.5	60.7

5.2 Main Results

VICO-actor consistently improves over the base model and outperforms three categories of baselines: RL-trained reasoning models, self- and co-evolution methods. Table 2 presents the main comparison. For the Chart Understanding variant, we report the OOD average over the eight benchmarks excluding ChartQA, which is its in-domain benchmark. For the CLEVR and ZwZ variants, all nine evaluation benchmarks are treated as out-of-domain. Notably, VICO attains these improvements using only 2000 seed inputs, which is $16\times-160\times$ fewer than the chart-specialized RLVR baselines that depend on large amounts of human or model-generated CoT annotations (Table 3). The strongest variant, VICO-8B (Chart), achieves the best OOD average accuracy of 64.9% (excluding in-domain ChartQA), improving over the base model by +5.0%. Against RL-trained reasoning baselines, VICO surpasses them by +15.5% on average. Against the strongest

Table 4: Visual edits outperform text-only perturbations. With the same CLEVR seed source, image editing in VICO improves the overall average by +6.1%, compared with +2.4% for text edits. The largest gap appears on ChartQA (+9.4% vs. +0.9%).

Benchmark	Base	VICO-Qwen3VL-8B (CLEVR, text-edit)	VICO-Qwen3VL-8B (CLEVR, image-edit)
<i>Mathematical reasoning</i>			
MathVista	67.7	70.3 $\pm$ 2.6 $\uparrow$	72.8 $\pm$ 5.1 $\uparrow$
MathVision	31.5	39.0 $\pm$ 7.5 $\uparrow$	41.0 $\pm$ 9.5 $\uparrow$
MathVerse	50.6	53.9 $\pm$ 3.3 $\uparrow$	56.0 $\pm$ 5.4 $\uparrow$
WeMath	72.0	73.1 $\pm$ 1.1 $\uparrow$	76.8 $\pm$ 4.8 $\uparrow$
LogicVista	55.1	54.1 $\pm$ 1.0 $\downarrow$	57.8 $\pm$ 2.7 $\uparrow$
<i>Chart reasoning</i>			
ChartQA	76.9	77.8 $\pm$ 0.9 $\uparrow$	86.3 $\pm$ 9.4 $\uparrow$
Overall avg.	59.0	61.4$\pm$2.4$\uparrow$	65.1$\pm$6.1$\uparrow$

Table 5: Iterative co-evolution beats static augmentation. Strong offline generators such as GPT-5 and Nano Banana improve ChartQA accuracy, but they remain below actor-conditioned visual co-evolution, which reaches 89.1%.

Setting	Iter. loop	Visual edit	ChartQA
Base (Qwen3-VL-8B)	–	–	76.9
<i>Static offline augmentation (no loop)</i>			
Offline-Random (self-gen)	✗	✓	78.6 $\pm$ 1.7 $\uparrow$
Offline-GPT-5	✗	✓	80.1 $\pm$ 3.2 $\uparrow$
Offline Nano Banana	✗	✓	81.9 $\pm$ 5.0 $\uparrow$
<i>RLVR-only (no environment adaptation)</i>			
Supervised GRPO	✗	✗	79.4 $\pm$ 2.5 $\uparrow$
Direct GRPO	✗	✗	83.8 $\pm$ 6.9 $\uparrow$
VICO-Qwen3VL-8B (Chart, text-edit)	✓	✗	77.2 $\pm$ 0.3 $\uparrow$
VICO-Qwen3VL-8B (Chart, image-edit)	✓	✓	89.1$\pm$12.2$\uparrow$

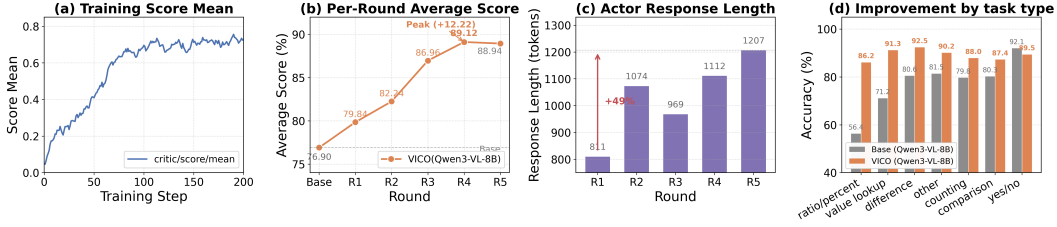


Figure 3: VICO trains stably and induces an emergent curriculum. (a) GRPO reward improves smoothly. (b) ChartQA accuracy peaks at Round 4 with a +12.2 gain. (c) Actor responses grow by +49%, suggesting harder tasks and longer reasoning. (d) Gains concentrate on reasoning-heavy question types.

self-evolution baseline (MM-Zero), the three VICO variants surpass it by +4.3% on the OOD benchmarks. Against the text-editing co-evolution baseline (V-Zero), VICO outperforms it by +8.4% on the overlapping benchmarks. Beyond open-source baselines, VICO-8B also outperforms Gemini-2-Flash and Gemini-2.5-Pro by +5.2% and +2.5% on the OOD benchmarks, showing that an 8B model trained through co-evolution can compete with much larger proprietary VLMs.

VICO has strong generalization across OOD domains and models. As shown in Table 2, VICO-8B variants gain +5.2% on average across OOD benchmarks. The transfer is strongest in mathematical reasoning: without math-specific training, VICO-8B (CLEVR), VICO-8B (Chart), and VICO-8B (ZwZ) improve over Qwen3-VL-8B by +5.5%, +5.4%, and +5.3% on MathVista, MathVision, MathVerse, WeMath, and LogicVista. This suggests that VICO learns transferable reasoning skills rather than domain-specific edit shortcuts. By comparison, existing RLVR baselines transfer less reliably: R1-OneVision-7B and MM-Eureka-Qwen-7B improve on one benchmark, but Qwen2.5-based RLVR baselines drop by -7.3% on average relative to their base models. VICO also transfers across backbones. Table 3 shows that VICO-Qwen2.5-VL-7B (Chart) and VICO-InternVL3-8B (Chart) improve over their base models by +4.7% and +7.1% on average.

Editing images is more effective than rewriting text alone. We compare visual-environment editing with text-only perturbation in Table 4. Within the same VICO environment, image editing yields a +6.1% gain in the evaluated reasoning benchmarks, while text-only perturbation improves by only +2.4%. The gap is especially clear on ChartQA, where image editing gains +9.4% versus only +0.9% for text-only perturbation. This finding is further supported by independent evidence: in the separately developed V-Zero framework, text-only perturbation also improves mathematical reasoning by only +1.8% over its base model. Together, these results show that the key bottleneck is the editing modality itself: effective co-evolution requires modifying the visual environment, not just rewriting the text.

VICO trains stably and improves across training rounds. Figure 3(a) shows that the step-wise GRPO training score increases smoothly without collapse or divergence. Across rounds, Figure 3(b) shows that VICO steadily improves on ChartQA. Accuracy rises from 76.9% at the base model to 89.1% at R4, giving a total gain of +12.2%. Each round contributes a positive gain. This improvement also appears at the sample level. Appendix Table 20 shows that R1 unlocks 13.9% test samples, and the cumulative unlocked fraction grows to 16.1% by R4. These results show that VICO accumulates new correct behaviors across rounds rather than reflecting round-specific fluctuations.

VICO’s Gains concentrate on reasoning-heavy question types. Figure 3(d) breaks down ChartQA accuracy by task type. The largest gains appear in multi-step reasoning, including ratio/percentage (+29.8%), value lookup (+20.1%), and difference (+11.9%). In contrast, visually simpler tasks improve less, such as comparison (+7.1%) and counting (+8.2%). The yes/no category slightly drops (−2.6%), likely because it is already saturated. These results suggest that VICO mainly improves reasoning-intensive skills rather than simply boosting easy visual recognition patterns.

VICO turns errors into correct answers with limited regression. To understand where the gain of round 4 comes from, we compare each sample’s correctness between the base model and our round 4 actor on the ChartQA test set (Appendix Table 19). VICO converts 365 samples from wrong to right (14.6%), while only 64 samples flip from right to wrong (2.6%). This gives an improvement-to-regression ratio of $5.7\times$. The net gain of 301 samples corresponds to +12.0%, closely matching the aggregate accuracy gain of +12.2%. Qualitatively, wrong-to-right cases often show explicit step-by-step decomposition, whereas the base model tends to give single-shot answers; examples are provided in Appendix I.5. These results show that the gains mainly come from newly acquired correct behaviors, not from trading off many previously correct samples.

5.3 Co-Evolution Dynamics, Capability Emergence, and Ablations

We then examine whether the actor–environment loop behaves as intended and whether this loop is the source of the gains.

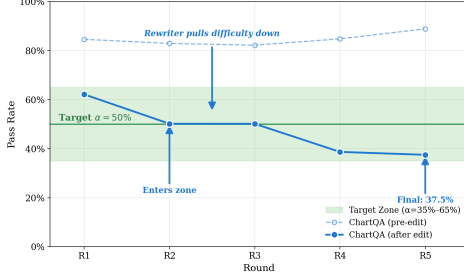
Both Rewriter SFT and the co-evolution loop are required. Table 6 separates the roles of supervised initialization and iterative co-evolution. Actor SFT alone improves ChartQA by only +2.5%, so stronger actor initialization cannot explain the full gain. Running the co-evolution loop with a vanilla EnvRewriter gives only +1.7%, because the Rewriter cannot effectively produce executable edit plans. Thus, the loop alone is also insufficient without a valid environment policy. The full +12.2% gain appears only when the EnvRewriter is SFT-initialized and then optimized through the iterative actor–environment loop. This shows that Rewriter SFT provides valid environment edits, while co-evolution turns those edits into actor-aligned training signals.

Table 6: Rewriter initialization is not enough; co-evolution unlocks the full gain. Actor SFT (w/o co-training) and a vanilla EnvRewriter give modest gains (+2.5% and +1.7%), while an SFT-initialized EnvRewriter optimized in the actor–environment loop reaches +12.2%.

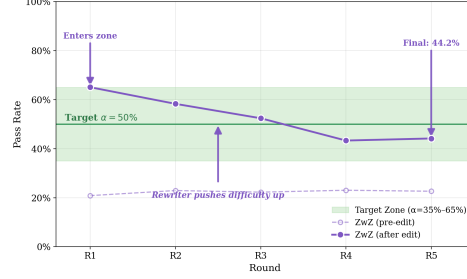
Baselines	ChartQA (Δ)
Base (Qwen3-VL-8B)	76.9
Actor SFT only	79.4 +2.5 $\uparrow$
Co-evolution (w/ Vanilla Re-writer)	78.6 +1.7 $\uparrow$
Co-evolution (VICO)	89.1 +12.2 $\uparrow$

The EnvRewriter learns bidirectional difficulty calibration. We compare two domains with opposite initial actor competence: ChartQA starts easy for the actor ($\hat{p}_{\text{orig}} \approx 0.85$), while ZwZ starts hard ($\hat{p}_{\text{orig}} \approx 0.21$). The EnvRewriter adapts in opposite directions. It makes ChartQA harder and lowers $\hat{p}_{\text{final}}$, while making ZwZ easier and raising $\hat{p}_{\text{final}}$. In both cases, $\hat{p}_{\text{final}}$ enters $[0.35, 0.65]$ within the first few rounds (Figure 4). This shows actor-relative calibration instead of random perturbation.

Stronger edits reflect learned decisions, not longer instructions. We next ask whether the EnvRewriter becomes a stronger editor across rounds. We measure edit intensity as $|\hat{p}_{\text{orig}} - \hat{p}_{\text{final}}|$, the pass-rate shift caused by an edit for the current actor. Edit intensity increases from 0.22 to 0.51, showing that the EnvRewriter changes task difficulty more effectively. This increase is not due to longer outputs: the average instruction length remains nearly unchanged (973 $\rightarrow$ 981 tokens) (Figure 10 in the Appendix). In contrast, the actor’s response length grows by +49% (Figure 3(c)), consistent with longer reasoning traces on harder tasks. These trends provide behavioral evidence of co-adaptation: the EnvRewriter produces more targeted edits, while the actor adapts with more elaborate reasoning. Additional analyzes are provided in Appendix I.2 and Appendix I.5.



(a) Strong ChartQA Actor: edits lower pass rate toward the sweet zone.



(b) Weak ZwZ Actor: edits raise pass rate toward the sweet zone.

Figure 4: **The EnvRewriter calibrates bi-directional difficulty.** On ChartQA, edits lower a strong Actor’s pass rate; on ZwZ, edits raise a weak Actor’s pass rate, moving both toward the sweet zone.

Table 7: **VICO remains robust under imperfect editing.** Training with 20% failed-edit images causes only a slight drop, showing that the co-evolution loop does not need a flawless image editor.

Baselines (↓)	Mathematical Reasoning						Vision-Centric				Overall
	MathVista	MathVision	ChartQA	MathVerse	WeMath	avg.	MMMU	MMVP	BLINK	avg.	avg.
Qwen3-VL-8B	67.7	31.5	76.9	50.6	72.0	59.8	55.8	77.7	68.9	67.5	63.6
Round1 (clean)	73.6	35.9	85.2	53.6	74.0	64.5	60.2	78.3	69.0	69.2	66.8
Round1 (noise-20%)	72.9	35.5	84.8	52.2	72.7	63.6	58.4	78.0	68.9	68.5	66.0

The iterative visual co-evolution loop drives the gains. We ablate whether the improvement comes from the co-evolution loop, the stronger offline data or RLVR-only training. First, we remove the loop and compare it against static offline augmentation. As shown in Table 5, stronger teachers improve the fixed corpus only modestly: Qwen3-VL-8B self-generation, GPT-5, and Nano Banana reach 78.64%, 80.10%, and 81.91% on ChartQA. All remain below 82%. In contrast, VICO-8B (Chart) reaches 89.12%, exceeding the strongest static method by +7.21%. Scaling the offline teacher from self-generation to Nano Banana gives only +3.27%, while adding the iterative loop gives +7.21%. Second, we keep the RLVR setup fixed but remove Rewriter-driven environment adaptation. Across all VICO variants, co-evolution outperforms Direct GRPO by +3.7% and Supervised GRPO by +4.8% on average. These results show that *the gains come from VICO’s iterative, difficulty-aligned actor-environment co-evolution.*

VICO is robust against imperfect image editing. Automatic image editors may produce blank images, unchanged images, or image-label mismatches. We therefore stress-test VICO by corrupting 20% of the R1 training data. As shown in Table 7, the overall average performance drops by less than 1%. The noisy model still remains well above the baseline model. This shows that VICO does not require a flawless image editor: failed edits do not dominate training, and the remaining valid samples are sufficient for stable co-evolution. Additional details in Appendix H.4.

Image-generator capability does not replace co-evolution. Our editing strategy must control difficulty while keeping labels verifiable. Simple perturbations, such as noise, rotation, or blur, can lower the Actor’s pass rate, but they mostly add perceptual noise and may shift samples away from the task distribution. Strong image generators produce better images, yet unconstrained generation can still cause answer drift or ambiguous labels. In contrast, VICO edits verifiable visual structures and preserves supervision through programmatic relabeling or answer-preserving editing. Thus, strong generators are useful backends, but not replacements for VICO: the core benefit is the actor-conditioned loop that selects, verifies, and re-aligns edits using rollout feedback. See Appendix K.

6 Conclusion

We present VICO, a co-evolution framework that reframes visual reasoning training as a dynamic, data-evolving co-evolution between an actor and an EnvRewriter, rather than a model-evolving process over a static corpus. By repurposing the rollout pass rate as a shared learning signal, VICO jointly trains an actor and an EnvRewriter that edits verifiable visual substructures toward the actor’s learning frontier, producing difficulty-calibrated training samples without any additional human

annotation. Across nine multimodal benchmarks, VICO consistently outperforms strong RLVR, self-evolution, and co-evolution baselines, generalizes to out-of-distribution tasks unseen during training, and remains stable across multiple VLM backbones, exceeding the strongest self-evolution baseline by +4.3% on out-of-domain tasks while using up to $160\times$ fewer labeled samples. Together, these results suggest that the bottleneck in visual reasoning post-training is *not the size of the static corpus but the fixed nature of the environment itself*, and that difficulty-aligned visual editing offers a scalable path forward in domains where high-quality human annotation is costly to obtain.

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A Limitations, Future Work, and Impact Statement

Limitations Although VICO shows strong empirical gains across multimodal reasoning benchmarks, several limitations remain. First, VICO relies on a verifiable image-side structure for editing. In CLEVR and ChartQA, this structure is provided by scene graphs or chart tables; in natural-image VQA, it is approximated by protected region masks. Extending the framework to visual domains without such structures or reliable region annotations remains an important direction.

Second, VICO introduces additional compute costs because each round estimates actor pass rates with multiple rollouts and updates both the actor and the EnvRewriter. This cost is higher than that of one-shot static augmentation, although it enables the training distribution to adapt to the actor’s evolving capabilities.

Third, our evaluation focuses on visual reasoning tasks with verifiable answers. Open-ended generation, dialog, and real-time interactive environments are outside the current scope. Future work can study adaptive difficulty targets, broader visual domains, and tighter integration with more general-purpose image editors.

Future work Future work can extend VICO to more complex multimodal tasks beyond static image reasoning. We plan to broaden the framework to tasks that require richer visual grounding, multi-image comparison, diagram reasoning, and tool-assisted multimodal problem solving. These settings require the environment to edit not only visual appearance but also higher-level task structure while preserving verifiable supervision.

Impact Statement VICO aims to reduce the reliance on large-scale human annotation for VLM post-training by turning existing visual data into adaptive, label-valid training samples. This may make visual reasoning training more scalable and accessible, especially in domains where high-quality annotations are expensive. At the same time, automatic image editing can introduce artifacts, biases, or label drift if used without verification. Our framework mitigates these risks through deterministic relabeling, answer-preserving constraints, and filtering, but careful validation remains necessary before applying similar systems to high-stakes domains.

B Implementation Details

B.1 VICO: Algorithm Details

Algorithm 1 VICO jointly updates the Actor and EnvRewriter from shared rollouts. Each round generates edited tasks, evaluates Actor rollouts, updates the Actor with task rewards, and updates the EnvRewriter with difficulty-calibration rewards.

Require: Actor π_a , EnvRewriter π_R , seed dataset $\mathcal{D}_{\text{seed}} = \{(x_i, q_i, a_i, \sigma_i)\}$, number of rounds T , rollouts per sample K , target pass rate α , difficulty filter threshold $k_{\min}$, RWR temperature λ

Ensure: Trained actor π_a , EnvRewriter π_R

Initialize actor pool $\mathcal{D}_a \leftarrow \emptyset$, EnvRewriter pool $\mathcal{D}_R \leftarrow \emptyset$

for round $t = 1, \dots, T$ **do**

Stage 1: Online Generation & Interaction

 Sample edit batch: $\mathcal{T}_t \leftarrow \{(x'_i, q'_i, a'_i)\}$ where $u_i \sim \pi_R(\cdot \mid x_i, \sigma_i)$, $x'_i = \mathcal{R}(u_i(\sigma_i))$

for each edited triple $(x'_i, q'_i, a'_i) \in \mathcal{T}_t$ **do**

 Sample K rollouts $\{\hat{a}_{i,k}\}_{k=1}^K$ from $\pi_a(\cdot \mid x'_i, q'_i)$

 Compute actor reward $R_{\text{actor}}(\hat{a}_{i,k}, a'_i)$ for each rollout

 Compute pass rate $\hat{p}_i \leftarrow k_i / K$

 Compute EnvRewriter reward $R_{\text{rewriter}}(\hat{p}_i)$

end for

Stage 2: Joint Update

 Update π_a via GRPO on $\mathcal{T}_t$ to maximize $\mathbb{E}[R_{\text{actor}}]$

 Filter: $\tilde{\mathcal{T}}_t \leftarrow \{(x_i, \sigma_i, u_i) : |\hat{p}_i - \alpha| \leq k_{\min}\}$

 Build weighted SFT set: $\tilde{\mathcal{D}}_R^t \leftarrow \{(x_i, \sigma_i, u_i, w_i) : w_i \propto \exp(\lambda R_{\text{rewriter}}(\hat{p}_i))\}$

 Update π_R via RWR on $\tilde{\mathcal{D}}_R^t$ to maximize $\mathbb{E}[R_{\text{rewriter}}]$

Stage 3: Aggregation

$\mathcal{D}_a \leftarrow \mathcal{D}_a \cup \text{Valid}(\mathcal{T}_t)$

$\mathcal{D}_R \leftarrow \mathcal{D}_R \cup \tilde{\mathcal{D}}_R^t$

end for

VICO trains an Actor and an EnvRewriter in an iterative actor–environment loop. The Actor learns from verifiable rollout rewards, while the EnvRewriter learns from the Actor’s empirical pass rate on its edited samples. The two models share a common pool of rollouts: each rollout simultaneously yields a task-level reward used to update the Actor and a difficulty signal used to update the EnvRewriter, enabling co-evolution without doubling the inference cost. The complete training loop is summarized in Algorithm 1 and described below.

Inputs and initialization The pipeline starts from a seed visual dataset $\mathcal{D}_{\text{seed}} = \{(x, q, a, \sigma)\}$, where x is the image, q is the question, a is the answer, and σ is a verifiable substructure when available, such as a CLEVR scene graph or a ChartQA data table. We initialize the Actor $\pi_a^{(0)}$ and the EnvRewriter $\pi_R^{(0)}$ from the same pretrained VLM family. The EnvRewriter is first SFT-initialized to produce executable edit commands. Four hyperparameters control the loop: the number of rounds T , the rollouts per sample K , the target pass rate α (we use $\alpha = 0.5$), the difficulty filter threshold $k_{\min}$ that discards edits whose pass rate is too far from α , and the RWR temperature λ that controls how sharply the EnvRewriter is biased toward high-reward edits. Two online pools, the Actor pool $\mathcal{D}_a$ and the EnvRewriter pool $\mathcal{D}_R$, are initialized empty and grow throughout training.

Stage 1: Online generation and interaction At the start of each round t , the EnvRewriter proposes a structured edit command $u_i \sim \pi_R(\cdot \mid x_i, \sigma_i)$ over the verifiable substructure σ_i for every seed instance. A domain renderer or editor produces the edited image $x'_i = \mathcal{R}(u_i(\sigma_i))$, and the answer a'_i is either computed programmatically from the edited structure or preserved by construction under the domain-specific validity rules in Appendix C. Thus, every retained sample is label-valid without model-based labeling. For each edited triple (x'_i, q'_i, a'_i) , the Actor samples K responses, and each response receives the rule-based Actor reward defined in Appendix B.4. We then compute the empirical pass rate $\hat{p}_i = k_i/K$, where k_i is the number of correct rollouts, and map it to the difficulty-calibration reward R_{rewriter} , which peaks when $\hat{p}_i$ matches the target α .

Stage 2: Joint update The two models are updated from the same batch of rollouts, but with different reward signals. Valid edited triples (x'_t, q'_t, a'_t) are used to update the Actor π_a via GRPO to maximize $\mathbb{E}[R_{\text{actor}}]$, leveraging the within-group advantage normalization that makes GRPO robust to scale differences across edits. The EnvRewriter π_R is updated via Reward-Weighted Regression (RWR): we first apply a difficulty filter, retaining only edits whose pass rate falls within $[\alpha - k_{\min}, \alpha + k_{\min}]$, and then construct a weighted SFT set in which each retained edit transition is weighted by $\exp(\lambda R_{\text{rewriter}})$. Fine-tuning π_R on this set biases it toward edits that land close to the target band. We additionally apply a KL penalty to the initial EnvRewriter and cap the per-step KL to prevent the editor from drifting into degenerate or off-distribution edit distributions.

Stage 3: Aggregation After each round, valid edited triples (those that render successfully and pass label-consistency checks) are appended to the Actor pool $\mathcal{D}_a$, while the weighted edit transitions are appended to the EnvRewriter pool $\mathcal{D}_R$. Both pools persist across rounds, so the Actor sees an increasingly diverse set of edited tasks, and the EnvRewriter learns from an increasingly informative history of difficulty signals. The updated Actor and EnvRewriter then become the starting point for the next round.

Why this differs from static RLVR? The key distinction from static RLVR is that the empirical pass rate $\hat{p}$ is not used only as a filtering statistic. It is also reused as an actor-relative supervision signal for the EnvRewriter, allowing the visual environment to track the Actor’s current capability. Crucially, the loop requires no new human-labeled QA: the seed representation σ_i provides the editable interface, and labels for edited samples are either recomputed or preserved through explicit validity constraints.

B.2 Actor GRPO Training Details

For the Actor π_a , we use GRPO with rule-based rewards. For each edited prompt, we sample multiple on-policy rollouts and score them with exact-match answer verification plus a format check. Unless otherwise stated, rollout sampling uses temperature 0.7, top- $p = 1.0$, and a maximum response length of 3,824 tokens, matching the zero-shot evaluation setting in the main text.

In the ChartQA multi-round runs, each round trains on approximately 1500–2500 EnvRewriter-generated modified training images, together with a fixed regularization set of 2,000 original ChartQA samples. The resulting Actor checkpoint initializes the next round.

B.3 EnvRewriter SFT and RWR Details

The EnvRewriter is trained in two stages. First, we initialize it with format-aware SFT on verified edit demonstrations generated by GPT-5. This stage teaches the model to produce structured, executable edit commands, use the available edit operations, and propose edits that adjust task difficulty while preserving label verifiability. Second, during co-evolution, we update the learned EnvRewriter using reward-weighted regression over valid edit transitions collected through interaction with the Actor.

For each executed edit, the current Actor produces K rollouts on the resulting sample. The empirical pass rate $\hat{p}$ is used to compute the edit’s RWR weight according to the bell-shaped difficulty objective in Appendix B.4. These weights are computed from the outcome of each edit turn. Invalid or unexecutable edits, as well as edits outside the RWR difficulty band, are excluded from the RWR target set. This encourages the EnvRewriter to concentrate its probability mass on valid edits near the Actor’s learnable zone. Actor training data are constructed separately: samples that satisfy execution and label-validity requirements may be retained even when their pass rates fall outside the RWR difficulty band.

GPT-5 as a strategic trajectory generator. We use GPT-5 to generate editing demonstrations for training the EnvRewriter. Given a seed sample, its editable structure, the current Actor’s empirical pass rate, the target difficulty band, and the domain-specific edit schema, GPT-5 proposes a structured edit command intended to adjust the task’s difficulty. The command is executed by the environment, and the resulting sample is evaluated by the Actor. The execution outcome and Actor feedback can then be included in the context for subsequent edits, producing actor-conditioned editing trajectories. GPT-5 provides the edit proposals, but it does not serve as the authority for either ground-truth labels or training rewards. Labels are obtained through domain-specific recomputation or checked for answer preservation, depending on the edit setting, while difficulty is measured using Actor rollouts. We construct the SFT dataset from executable, verified demonstrations whose edits move the Actor’s pass rate closer to the target pass rate. These demonstrations supervise both the edit-command format and the choice of editing strategies.

EnvRewriter interface. The EnvRewriter is an LVLM policy initialized from the same model family as the Actor and SFT-initialized to produce executable edit commands. Its input contains the image, question, answer, editable structure σ , current Actor pass rate $\hat{p}$, target pass rate α , and the domain-specific tool schema. Its output is a structured tool call with fields `tool`, `params`, and `reasoning`. For example, in ChartQA, the EnvRewriter may output a `chart_rerender` command that edits the underlying CSV table and re-renders the chart. The command is executed by the domain renderer or image editor, and the resulting sample is kept only if it passes the validity checks in Table 1. Full prompts and tool schemas are provided in Appendix F.4.

B.4 Reward Functions and Difficulty Filtering

Actor Reward. The Actor reward is defined as:

$$R_{\text{actor}}(q', o) = \begin{cases} +1, & \text{if FormatCorrect}(o) \wedge \text{AnswerCorrect}(o), \\ -1, & \text{otherwise.} \end{cases} \quad (\text{B.1})$$

EnvRewriter Reward. For each executed edit, the empirical pass rate on the resulting sample is $\hat{p} = k/K$, where k is the number of correct Actor rollouts under R_{actor} . The EnvRewriter reward is:

$$R_{\text{rewriter}}(\hat{p}) = \exp(-\beta(\hat{p} - \alpha)^2), \quad (\text{B.2})$$

where $\beta > 0$ controls sharpness. We use $\alpha = 0.5$, $\beta = 4.0$, and $k_{\min} = 0.15$ for the difficulty filter.

Difficulty filter. The reward encourages edits whose resulting samples have pass rates near the Actor’s learning frontier. In practice, we keep a sweet-zone band around $\alpha = 0.5$ and discard invalid or poorly calibrated edits from EnvRewriter updates. This prevents the EnvRewriter from overfitting to samples that are already solved or impossible for the current Actor.

B.5 Hyperparameters

Table 8: **VICO uses one compact training recipe.** Unless stated otherwise, the same core hyperparameters are used across visual domains.

Component	Value
Actor optimizer	AdamW
Actor update	GRPO
Actor learning rate	1×10^{-6}
Rollouts per sample	$K = 8$ for pass-rate estimation
Sampling temperature	0.7
Top- p	1.0
Maximum response length	3,824 tokens
EnvRewriter update	Reward-weighted LoRA SFT / RWR
Difficulty target	$\alpha = 0.5$
Reward sharpness	$\beta = 4.0$
Sweet-zone band	$[0.35, 0.65]$ unless otherwise stated
Training rounds	Up to 5 rounds
Hardware	Up to $8 \times \text{A100-80GB}$ GPUs
Training framework	verl-based distributed RL training

Table 9: **RWR trains the EnvRewriter with pass-rate-weighted edit transitions.** We train LoRA on Qwen3VL-8B-Instruct using LlamaFactory. Each retained edit transition is duplicated $\lfloor 5 \cdot w(\hat{p}) \rfloor$ times based on the Actor pass rate $\hat{p}$ on the sample produced by that edit turn.

Model & LoRA		Optimization	
base model	Qwen3VL-8B-Instruct	learning rate	5.0×10^{-6}
template	qwen3_vl	scheduler	cosine
finetuning type	LoRA	warmup ratio	0.1
LoRA rank	64	total epochs	10
LoRA alpha	128	per-device batch	2
LoRA target	all	grad. accum. steps	8
precision	bf16	effective batch	64
Eval & Checkpointing		RWR Data Construction	
eval strategy	steps	RWR weight α	0.5
eval/save steps	50 / 50	RWR weight β	4.0
save total limit	3	max sample repeats	5
load best model	true	weight formula	$\exp(-\beta(\hat{p} - \alpha)^2)$
best metric	eval_loss	number of GPUs	4

RL training parameters. We optimize the actor with reinforcement learning to improve multi-step visual reasoning.

B.6 Compute and Hardware

All experiments use distributed training on up to $8 \times \text{A100-80GB}$ GPUs. We use a VERL-based implementation for GRPO training and parallel rollout generation. A detailed cost and annotation-efficiency comparison is provided in Appendix G.3.

C Data Sources and Verifiable Visual Editing

This appendix describes how VICO produces label-valid training samples across three visual domains. The key point is that different domains provide different forms of verifiability.

For CLEVR, VICO edits an explicit scene graph and recomputes the answer programmatically by executing the original question program. For ChartQA, VICO edits the underlying CSV table and uses a two-tier verification rule: Tier 1 recovers the new answer by entity-anchored lookup in the edited

Table 10: **GRPO trains the Actor with rollout-level verifiable rewards.** We train Qwen3VL-8B-Instruct with verl and a vLLM rollout backend. We disable KL penalty in reward shaping and loss to avoid gradient interference, following [31].

<i>Model & Reward</i>		<i>Rollout & Batch</i>	
base model	Qwen3VL-8B-Instruct	rollouts per prompt, N	8
algorithm	GRPO	train batch size	32
reward manager	binary	PPO mini-batch	8
KL in reward	False	PPO micro-batch/GPU	1
KL loss coeff.	0	log-prob micro-batch/GPU	1
entropy coeff.	0	rollout backend	vLLM
		tensor model parallel	1
		sampling temperature	0.7
<i>Optimization</i>		<i>Sequence Limits & Schedule</i>	
actor learning rate	1.0×10^{-6}	max prompt length	1,048
scheduler	cosine	max response length	3,824
warmup ratio	0.05	max model length	6,896
total epochs	3	max batched tokens	16,392
precision	bf16	truncation	left
grad. checkpointing	enabled	filter overlong prompts	True
FSDP strategy	FSDP2	save / val freq	50 / 20
sequence parallel size	1	validate before training	True
number of GPUs	8		

table, while Tier 2 keeps CSV values fixed and preserves the original answer by construction. For natural-image VQA, where no complete symbolic state is available, VICO uses answer-preserving regional editing: the question and answer remain fixed, while the EnvRewriter edits only non-target visual regions.

Thus, VICO uses two label-validity mechanisms: deterministic recomputation when the answer can be derived from the edited structure, and constrained answer preservation when the answer-bearing structure must remain fixed.

C.1 Seed Data Sources

VICO uses a small seed set to initialize each visual reasoning domain. For compositional reasoning, we sample CLEVR images with their scene graphs and question programs. For chart reasoning, we sample ChartQA training images together with their underlying data tables. For natural-image VQA, we sample ZwZ images, which provide answer-relevant region annotations. We use these regions to identify target objects and preserve the original question-answer pair during editing.

C.2 Overview of the Three Editing Arms

Table 11 summarizes the three editing arms. CLEVR supports full deterministic answer recomputation from the edited scene graph. ChartQA uses a two-tier table rule: Tier 1 updates the answer by entity-anchored lookup in the edited CSV table, while Tier 2 preserves the answer under constrained table edits. The natural-image VQA arm follows a different rule: it keeps the original question and answer unchanged and only edits regions outside the answer-relevant target objects.

C.3 CLEVR: Scene-Graph Editing

For CLEVR, the editable structure σ is the scene graph paired with each image. Each scene graph specifies a set of objects, with each object carrying attributes such as `shape`, `color`, `material`, and `size`, as well as pairwise spatial relations such as `left-of`, `right-of`, `front`, and `behind`. Questions are generated from question-program templates over the scene graph, so the same program can be re-executed on the edited graph to produce a' .

Edit operations. The EnvRewriter outputs an edit command u in one of four categories: (i) **attribute change**, which modifies the `color`, `material`, or `size` of a target object; (ii) **category swap**,

Table 11: **VICO uses three editing arms for verifiable visual variation.** CLEVR recomputes answers from scene graphs, ChartQA uses a two-tier table rule, and ZwZ preserves answers by protecting target objects.

Arm	Editing interface	Answer rule
CLEVR	Scene graph edits over objects, attributes, and relations; rendered with Blender.	Recompute a' by re-executing the question program.
ChartQA	CSV/table edits rendered with matplotlib.	Tier 1: entity-anchored lookup; Tier 2: keep $a' = a$ under constrained edits.
ZwZ	SAM3 masks with protected target objects; edit only non-target regions.	Keep $q' = q$ and $a' = a$ under target-object protection.

which changes an object’s shape among cube, sphere, and cylinder; (iii) **entity add/remove**, which inserts or deletes objects while preserving renderability; and (iv) **relation modification**, which repositions objects to alter spatial relations. Each operation acts on the scene graph rather than on pixels, so $u(\sigma)$ remains a fully specified renderable scene.

Renderer. We use Blender with the original CLEVR rendering script to produce $x' = \mathcal{R}(u(\sigma))$. Camera parameters, lighting, and material shaders are kept consistent with the original rendering pipeline to avoid stylistic drift.

Answer derivation. We retain the original question program and re-execute it on $u(\sigma)$ to obtain a' . For example, if the original program is `count(filter(color=red, shape=cube))` and the edit changes one red cube into a blue cube, the new answer decreases by one. Because program execution on a discrete scene graph is exact, CLEVR samples are label-valid by construction.

Failure mode. An edit is discarded if it makes the question ambiguous or non-executable. For example, if an edit creates multiple possible referents for a question that assumes a unique object, the sample is removed before training.

C.4 ChartQA: Table-Level Editing and Re-rendering

For chart reasoning, the editable structure σ is the CSV table underlying each chart. The EnvRewriter edits the table-level representation rather than chart pixels, and matplotlib re-renders the edited table into a new chart image. This allows VICO to adjust visual and numerical difficulty while keeping label validity controlled by the table.

Tier construction. For each ChartQA seed sample, we first apply an automatic label-to-cell matching heuristic. We scan the CSV table and match value cells against the original answer. If exactly one cell matches, the sample is assigned to Tier 1. Let (r^*, j^*) denote the matched answer cell, and let e^* denote the row entity at r^* in the original table. If no cell matches, or multiple cells match, the sample is assigned to Tier 2. Tier 2 often includes derived-answer cases such as ratios, percentages, or differences, or ambiguous duplicate values.

Edit operations. For Tier 1, the EnvRewriter may modify table values, add near-match distractor rows, increase chart density, or sharpen contrasts. After editing, the answer is recovered by entity-anchored lookup in the edited table:

$$a' = \text{table}'[\text{entity} = e^*, j^*].$$

This lookup avoids relying on the original row index after row insertion or reordering. For Tier 2, the EnvRewriter keeps CSV values fixed and only varies rendering style or other answer-preserving visual factors. The label is therefore kept as $a' = a$ by construction.

Renderer. We re-render charts with matplotlib using the same chart type and style configuration as the source chart whenever possible, including chart type, color palette, axis labels, fonts, and gridlines.

Failure mode. We discard edits that violate the table schema, remove or duplicate the Tier 1 anchor entity e^* , remove the target column j^* , produce no numeric columns, fail rendering, or break the Tier 2 invariance constraint by changing CSV values. Numerical edits are bounded to keep the rendered chart visually plausible.

C.5 ZwZ: Answer-Preserving Natural-Image Editing

For natural-image VQA, VICO does not attempt to recompute a new answer from a full symbolic scene representation. Instead, it preserves the original question-answer pair. Given a seed sample (x, q, a) , the edited sample is (x', q, a) , where $q' = q$ and $a' = a$.

The key assumption is that the answer is grounded in a set of answer-relevant target objects. ZwZ provides answer-relevant region annotations, and we use SAM3 to decompose the image into object-level masks. Masks that overlap the answer-relevant region are treated as **target objects**. These target objects form the protected region σ^+ . All other object masks and background regions form the editable complement σ^- .

Edit operations. The EnvRewriter receives the image, question, answer, object masks, protected target objects, and current Actor pass-rate signal. It then proposes edits restricted to σ^- . Typical edits include adding distractor objects outside the target region, modifying background clutter, changing the appearance of non-target objects, or introducing visually plausible distractors that do not alter the answer-relevant target objects. The EnvRewriter is not allowed to edit, occlude, remove, or semantically change the protected target objects.

Rendering. The original image, the protected target-object mask, and the edit command are passed to an external image editor. The editor modifies only the editable complement and returns the edited image x' . Unlike CLEVR or ChartQA, this step is not treated as deterministic symbolic rendering. It is an answer-preserving image-editing step under a protected-region constraint.

Answer rule. For ZwZ, the answer is not recomputed. We keep the original question and answer:

$$q' = q, \quad a' = a.$$

The Actor reward therefore compares the model’s prediction against the original answer a . This distinguishes natural-image VQA from the structured arms, where a' is programmatically recomputed.

Failure mode. An edit is discarded if it touches the protected target objects, changes the visual evidence needed to answer the question, or introduces new content that would make the original answer ambiguous. For example, if the question depends on counting target objects, adding another object of the same relevant category is rejected. If the question depends on a spatial relation involving a target object, edits that change that relation are rejected. This conservative filtering keeps the natural-image VQA arm answer-preserving rather than relabeled.

C.6 Filtering Invalid or Ambiguous Edits

Across all editing arms, we discard edits that fail label-validity or execution checks.

First, the edited sample must be executable by the corresponding renderer or image editor. For CLEVR, the scene graph must render successfully in Blender. For ChartQA, the edited CSV must satisfy the table schema and render successfully with matplotlib. For ZwZ, the image editor must preserve the protected target-object region.

Second, the edited sample must preserve a valid answer. For CLEVR, the question program must be executable on the edited scene graph to compute a' . For ChartQA Tier 1, the anchor entity e^* and target column j^* must remain valid and addressable in the edited table so that $a' = \text{table}'[\text{entity} = e^*, j^*]$ can be recovered by lookup. For ChartQA Tier 2, the edit must satisfy the invariance constraint: CSV values remain fixed and the original answer is kept as $a' = a$. For ZwZ, the original answer remains valid because protected target regions are not edited.

Third, the edited sample must provide useful difficulty for the current Actor. We measure this by the empirical pass rate $\hat{p}$ after Actor rollouts. Invalid, ambiguous, unexecutable, or out-of-band edits are removed from the EnvRewriter update set.

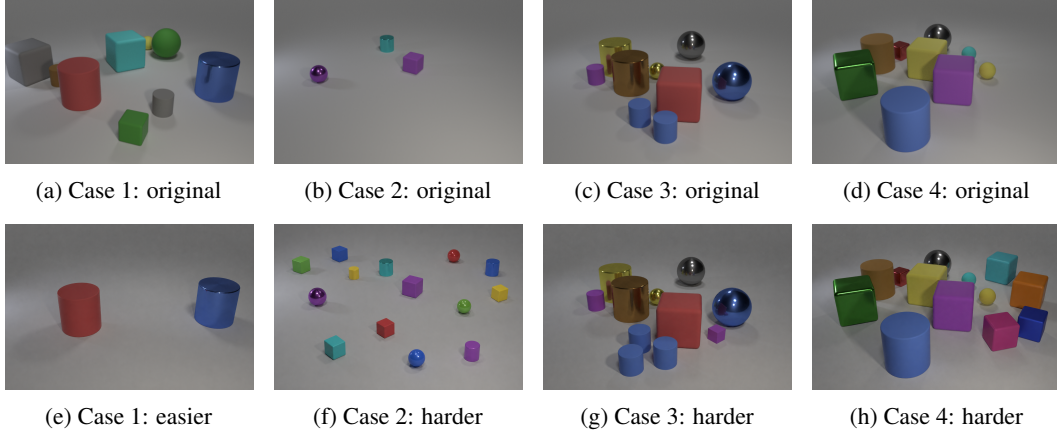


Figure 5: **CLEVR edits change difficulty while preserving verifiable labels.** Each column shows one case before and after editing. The EnvRewriter modifies the scene graph, re-renders the image, and recomputes a' by executing the original question program on the edited graph.

C.7 Dataset and Edited Sample Visualizations

Figures 5, 6, and 7 show representative visual examples for the three editing arms. For CLEVR, edits are applied to a scene graph and the answer a' is recomputed by executing the original question program. For ChartQA, Tier 1 examples recover a' by entity-anchored lookup in the edited CSV table, while Tier 2 examples preserve $a' = a$ through constrained table edits. For ZwZ, the original question and answer are retained, while answer-relevant target objects are protected and only non-target regions are edited. Together, these examples show the two label-validity mechanisms used by VICO: deterministic recomputation when an answer can be derived from the edited structure, and constrained answer preservation when the answer-bearing structure must remain fixed.

C.8 Robustness to Tool Failures and Difficulty Alignment as the Bottleneck

Renderer or editor failures may produce non-renderable scenes, invalid charts, or protected-region violations. In VICO, these failures are filtered before EnvRewriter updates: invalid, label-breaking, or out-of-band edits contribute no gradient to π_R . This biases the EnvRewriter toward edit plans that are executable, label-valid, and useful for the current Actor. Appendix H.4 further stress-tests this assumption by corrupting 20% of R1 training data and shows that performance drops by less than one point.

D Image Editing Case Studies

D.1 CLEVR Scene-Graph Editing Examples

Figure 5 shows representative CLEVR edits. Each example starts from a seed scene and applies a structured edit to object attributes, object categories, object counts, or spatial relations. Because the edit is applied to the scene graph rather than directly to pixels, the modified scene remains renderable, and the answer can be recomputed by program execution. These examples illustrate how VICO produces label-valid visual perturbations instead of relying on model-based relabeling.

D.2 ChartQA Table-Level Editing Examples

We present the ChartQA edits shown in Figure 6. Each seed sample is associated with an underlying data table, a question q , and an original answer a . Conditioned on the current Actor pass rate $\hat{p}$, the EnvRewriter generates a table-level edit aimed at the desired difficulty. To make the sample harder, it may add near-match rows, distractor series, or more confusable values; to make it easier, it may remove distractors or sharpen relevant contrasts. The edit is applied to table to produce table', which is then re-rendered into a new chart.

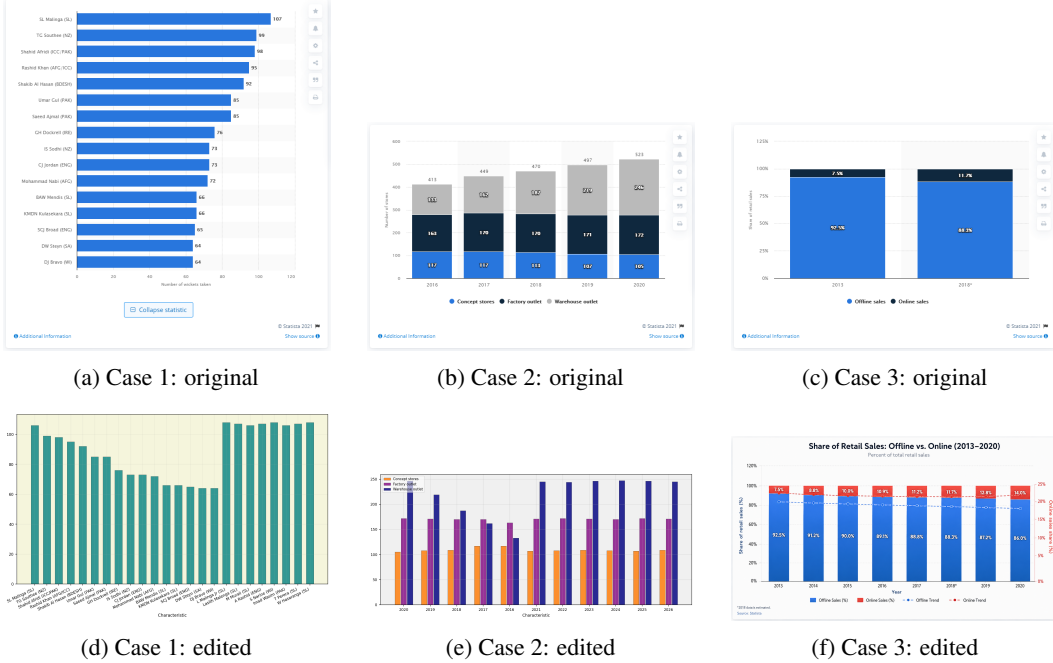


Figure 6: **ChartQA edits increase difficulty through table-level changes.** Each column shows one case before and after editing. The EnvRewriter modifies the CSV-level representation and re-renders the chart. For Tier 1 examples, a' is recovered by entity-anchored lookup in the edited table; for Tier 2 examples, CSV values are kept fixed and $a' = a$ is preserved by construction.

We use the same two-tier verification rule as in Table 1. For Tier 1 samples, the answer maps to a unique CSV cell (r^*, j^*) . Let e^* denote the row entity at r^* in the original table. After editing, the new answer is recovered by entity-anchored lookup:

$$a' = \text{table}'[\text{entity} = e^*, j^*].$$

This avoids relying on the original row index after rows are inserted or reordered.

For Tier 2 samples, the answer has no unique cell mapping, such as no match or multiple matches. These cases often include derived quantities such as ratios, differences, or percentages. For Tier 2, the EnvRewriter keeps CSV values fixed and only varies rendering style or other answer-preserving visual factors, so the label remains $a' = a$ by construction. In both tiers, no human relabeling or LLM judgment is used.

D.3 ZwZ Answer-Preserving Regional Editing Examples

Figure 7 shows representative ZwZ examples. Unlike CLEVR and ChartQA, ZwZ does not provide a complete symbolic state for deterministic relabeling. Thus, VICO keeps the original question-answer pair fixed, i.e., $q' = q$ and $a' = a$. We use SAM3 [5] to identify object-level regions and mark the answer-relevant target objects as protected. The EnvRewriter then edits only non-target regions, such as background areas or distractor objects, to adjust visual difficulty while preserving the evidence needed to answer the original question.

These examples highlight the difference between structured editing and natural-image regional editing. For CLEVR, labels are recomputed by executing the original question program on the edited scene graph. For ChartQA, labels are handled by a two-tier rule: Tier 1 computes a' by entity-anchored lookup in the edited CSV table, while Tier 2 preserves $a' = a$ by keeping CSV values fixed and only changing answer-preserving visual factors. For ZwZ, labels are preserved by protecting answer-relevant regions and editing only non-target visual context.

D.3.1 What Happens without Answer Preservation?

A natural alternative is to directly ask a generative image model to produce an easier or harder image. However, this often breaks answer preservation. Figure 8 shows one example. The original question

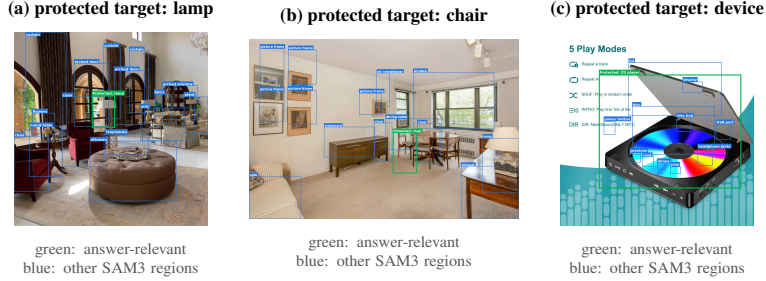


Figure 7: **ZwZ edits preserve answers by protecting target objects.** Green boxes mark answer-relevant targets, and blue boxes show other SAM3 regions. VICO keeps ($q' = q, a' = a$) fixed and edits only non-target regions, allowing background difficulty to change while preserving the original answer.

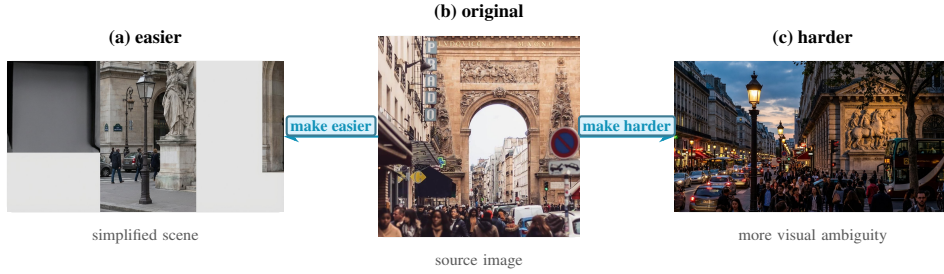


Figure 8: **Direct Nano Banana editing can break answer validity.** Starting from the original image, direct generation can produce easier or harder variants, but the edits may change target relations or introduce ambiguous objects. As a result, the original question-answer pair may no longer be verifiable.

asks: “Where is the street lamp in relation to the sculpture?” The original answer is “left of.” After direct generation with Nano Banana, the newly generated answer becomes “right of.”

This edit is problematic because the generated image no longer has a clearly verifiable target relation. There are multiple street lamps and multiple sculpture-like objects, so it is unclear which pair the answer refers to. The image may look visually plausible, but the question-answer pair is no longer label-valid. This illustrates why our editing pipeline explicitly enforces answer preservation: the edited image should change visual difficulty while keeping the answer-relevant objects and their relation verifiable.

D.3.2 What Improves with VICO

As shown in Figure 9, this example illustrates how VICO edits a ZwZ image while preserving answer validity. Starting from the original image in (d), VICO first identifies all objects in the scene, as shown in (c). It then selects and locks the answer-relevant target objects mentioned in the question, shown in (b). In this example, the target objects are the street lamp and the sculpture, whose relative relation determines the answer.

After locking these target objects, VICO edits only the non-target regions. This allows the model to simplify the scene by removing distracting content, such as the crowd and traffic signs, while keeping the answer-relevant objects unchanged. The final edited image is shown in (a). The task becomes visually easier, but the answer remains clean and verifiable because the key objects and their spatial relations are preserved throughout the editing process.

E Theoretical Analysis and Saturation

This appendix presents the full derivation of the optimal difficulty target $\hat{p}_t^*$ that motivates the sweet-zone reward.

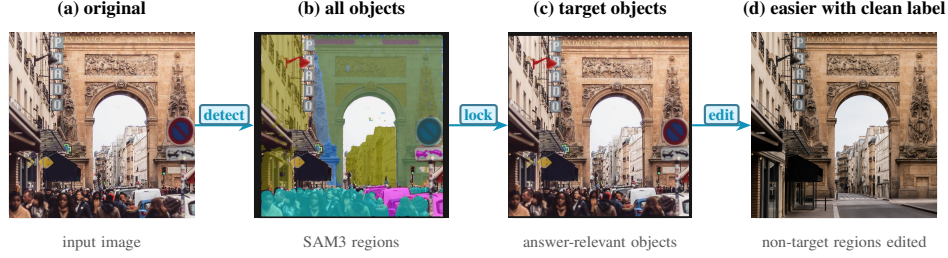


Figure 9: **VICO makes ZwZ easier while preserving the answer.** The pipeline detects object regions, locks the answer-relevant targets, and edits only non-target regions. This changes visual difficulty while keeping the original spatial relation and answer verifiable.

E.1 Gradient-Signal Optimum

Under a REINFORCE-style policy gradient estimator [33], the expected gradient signal for a sample with Actor pass rate $\hat{p}$ is proportional to

$$G(\hat{p}) = \hat{p}(1 - \hat{p}), \quad (\text{E.1})$$

which is a concave quadratic maximized at $\hat{p}^* = 0.5$. Tasks that are too easy ($\hat{p} \rightarrow 1$) or too hard ($\hat{p} \rightarrow 0$) provide weak learning signals; half-correct tasks maximize gradient information. This motivates a single-point target $\hat{p}^* = 0.5$ in agent-environment co-evolution under standard assumptions.

Derivation of Eq. E.1. Let $y \sim \pi_\theta(\cdot | x)$ be a sampled solution, and let the verifier return a binary reward $R(y) \in \{0, 1\}$. Define the actor pass rate as

$$p = \Pr(R = 1).$$

Because R only takes values 0 and 1, it follows a Bernoulli distribution:

$$R \sim \text{Bernoulli}(p), \quad \mathbb{E}[R] = p.$$

Using the REINFORCE estimator with the variance-minimizing baseline $b = \mathbb{E}[R] = p$ [20], we have

$$\nabla_\theta J(\theta) = \mathbb{E}[(R - p) \nabla_\theta \log \pi_\theta(y | x)].$$

Since $R \sim \text{Bernoulli}(p)$, we split the expectation into success and failure cases:

$$\begin{aligned} \nabla_\theta J(\theta) &= \Pr(R=1)(1 - p) \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=1] \\ &\quad + \Pr(R=0)(0 - p) \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=0]. \end{aligned}$$

Using $\Pr(R=1) = p$ and $\Pr(R=0) = 1 - p$, we obtain

$$\begin{aligned} \nabla_\theta J(\theta) &= p(1 - p) \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=1] \\ &\quad + (1 - p)(-p) \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=0]. \end{aligned}$$

Factoring out $p(1 - p)$ gives

$$\nabla_\theta J(\theta) = p(1 - p) (\mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=1] - \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=0]).$$

Defining

$$\Delta = \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=1] - \mathbb{E}[\nabla_\theta \log \pi_\theta(y | x) | R=0],$$

we conclude

$$\nabla_\theta J(\theta) = p(1 - p)\Delta. \quad (\text{E.2})$$

Under the trust-region KL constraint and gradient-clipping bias of GRPO-style updates [31], the conditional log-policy gradients in Δ stay within a bounded range across $R \in \{0, 1\}$, so $\|\Delta\|$ contributes only a bounded multiplicative constant. The strength of the learning signal is therefore proportional to $p(1 - p)$, recovering Eq. E.1.

E.2 Distribution Drift Cost

The single-point analysis implicitly assumes that adjusting task difficulty incurs no cost. This holds for text-agent settings where generating a harder task does not change the task’s distributional form. In visual reasoning, however, the EnvRewriter must edit images to shift $\hat{p}$ from its original value $\hat{p}_{\text{orig},t}$ toward the target. As the Actor strengthens and $\hat{p}_{\text{orig},t}$ rises, reaching $\hat{p} = 0.5$ requires increasingly aggressive edits that push the training distribution away from the natural image distribution [4, 1]. The Actor may then learn patterns specific to these distorted images that do not transfer back to the real test set.

We model this trade-off by decomposing each round’s expected accuracy gain into a learning-signal term and a distribution-drift penalty:

$$\Delta \text{Acc}_t = C_t \cdot G(\hat{p}) - \lambda \cdot D_t(\hat{p}), \quad (\text{E.3})$$

where $C_t > 0$ denotes the Actor’s remaining capacity headroom at round t , $D_t(\hat{p})$ captures the generalization cost of shifting the training distribution, and $\lambda > 0$ controls the Actor’s sensitivity to distribution drift. The single-point analysis corresponds to the special case $D_t \equiv 0$.

We adopt the simplest convex form for the drift cost:

$$D_t(\hat{p}) = \kappa_t \cdot (\hat{p} - \hat{p}_{\text{orig},t})^2, \quad (\text{E.4})$$

which satisfies three natural properties: zero cost when no editing occurs, monotonically increasing cost with larger deviations, and increasing marginal cost. More general convex forms $D_t = \kappa_t |\hat{p} - \hat{p}_{\text{orig},t}|^q$ with $q \geq 1$ yield qualitatively identical conclusions.

E.3 Optimal Difficulty Target

Substituting Eqs. E.1 and E.4 into Eq. E.3 and taking the derivative with respect to $\hat{p}$,

$$\frac{d \Delta \text{Acc}_t}{d \hat{p}} = C_t(1 - 2\hat{p}) - 2\lambda\kappa_t(\hat{p} - \hat{p}_{\text{orig},t}) = 0.$$

Solving yields

$$\hat{p}_t^* = \frac{C_t + 2\lambda\kappa_t \cdot \hat{p}_{\text{orig},t}}{2C_t + 2\lambda\kappa_t}. \quad (\text{E.5})$$

Defining $\rho_t = \frac{\lambda\kappa_t}{C_t + \lambda\kappa_t} \in [0, 1]$, this rearranges to a convex combination:

$$\hat{p}_t^* = \frac{1}{2} + \rho_t \cdot \left(\hat{p}_{\text{orig},t} - \frac{1}{2} \right). \quad (\text{E.6})$$

The optimal target is a weighted interpolation between 0.5 and the current $\hat{p}_{\text{orig},t}$, with the weight ρ_t determined by the ratio of drift cost to remaining capacity.

E.4 Two Limiting Regimes

Equation E.6 unifies two extremes.

Early-stage ($\rho_t \rightarrow 0$, i.e., $C_t \gg \lambda\kappa_t$). The Actor has ample capacity headroom, and light editing suffices to reach the target zone. The optimal target approaches 0.5, recovering the gradient-signal optimum. In this regime, difficulty calibration should be aggressive.

Saturation regime ($\rho_t \rightarrow 1$, i.e., $C_t \rightarrow 0$). The Actor is near its capacity ceiling [48]; reaching $\hat{p} = 0.5$ would require extreme edits whose drift cost exceeds the learning benefit. The optimal target shifts toward $\hat{p}_{\text{orig},t}$, meaning the EnvRewriter should reduce its editing intensity. Continued training in this regime enters a drift-dominated phase where further editing degrades rather than improves performance.

E.5 From Theory to the Sweet-Zone Reward

In practice, C_t and κ_t are not directly observable, making it infeasible to track $\hat{p}_t^*$ exactly. We instead define a sweet zone $[0.35, 0.65]$ centered at 0.5 as a robust approximation. The Gaussian

Table 12: **Sweet-zone hits decline as the Actor approaches saturation.** The fraction of EnvRewriter trajectories in $[0.35, 0.65]$ falls monotonically as the Actor matures, matching the saturation regime predicted by Eq. E.6.

Round	Sweet-zone hit rate (%)
R1	53.4
R2	29.5
R3	21.2
R4	20.5
R5	11.1

reward $R_R(\hat{p}) = \exp(-\beta(\hat{p} - 0.5)^2)$ peaks at 0.5 but assigns substantial weight to nearby pass rates, absorbing the drift of $\hat{p}_t^*$ across rounds without requiring direct estimation of ρ_t . The empirical saturation patterns in Appendix E.6 provide direct evidence that VICO’s training dynamics align with the regime predicted by Eq. E.6.

E.6 Empirical Saturation Evidence

VICO keeps improving through R4 and reaches 89.12% on ChartQA. At R5, accuracy slightly retreats to 88.94%. This is not a training failure but the saturation regime predicted by the drift-corrected analysis. Once the Actor approaches its capacity ceiling, the optimal target $\hat{p}_t^*$ drifts away from 0.5, and forcing the original sweet zone begins to hurt rather than help. The analysis predicts four signatures of saturation, all of which are verified empirically.

Table 13: **ChartQA gains diminish as co-evolution saturates.** Accuracy improves through R4, while round-over-round gain Δ shrinks and turns slightly negative at R5, consistent with the saturation regime predicted by our drift-corrected theory.

Round	ChartQA (Qwen3-VL-8B)	Δ
Base	76.90	—
R1	85.24	8.34
R2	87.50	2.26
R3	88.47	0.97
R4	89.12	0.65
R5	88.94	−0.18

Signature 1: The optimal target drifts away from 0.5. The EnvRewriter pulls $\hat{p}$ into the sweet zone in early rounds. But the target itself does not stay still. As the Actor strengthens, the optimal $\hat{p}_t^*$ shifts away from 0.5 toward $\hat{p}_{\text{orig},t}$ because forcing a 50% success rate would require edits whose drift cost outweighs their learning benefit. The EnvRewriter follows this shift: $\hat{p}$ moves from 0.502 at R3 to 0.375 at R5, tracing the predicted trajectory $\hat{p}_t^* \rightarrow \hat{p}_{\text{orig},t}$ as $\rho_t \rightarrow 1$.

Signature 2: Useful training signals become scarce. The fraction of edits landing in $[0.35, 0.65]$ decays monotonically from 53.4% at R1 to 11.1% at R5. Most edits no longer land in the trainable band, so each round delivers a weaker gradient signal even though the EnvRewriter still produces edits at the same rate.

Signature 3: Per-round gains decay smoothly. The full trajectory of round-over-round improvements is +8.34, +2.26, +0.97, +0.65, and −0.18. This traces the smooth deceleration expected as $C_t \rightarrow 0$, rather than a sudden collapse.

Signature 4: Categories with the least headroom regress first. The main text identifies value_lookup and ratio_pct as two question types that gained most through R4. These large prior gains mean these categories have less remaining headroom, and at R5 they are the first to regress, while categories with smaller earlier gains remain stable. This selective regression is consistent with the target-drift mechanism in Eq. E.6.

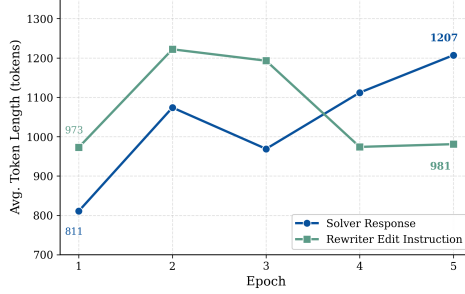


Figure 10: **EnvRewriter edit length stays stable.** Multi-round training improves edit strength without making edit instructions longer.

Together, these four trajectories indicate that R5 marks entry into a drift-dominated regime. The fixed sweet zone $[0.35, 0.65]$ that works through R4 is no longer aligned with the moving optimal target $\hat{p}_t^*$. This points to a concrete next step: rather than holding the difficulty band fixed, future work should schedule α adaptively or widen the trainable band as the Actor matures.

E.7 Pass-Rate Distribution Shift

The empirical pass-rate distribution shifts across rounds. Early rounds concentrate near $\alpha = 0.5$, while later rounds increasingly drift toward the extremes. This distributional shift explains why the sweet-zone hit rate decays and why additional rounds eventually yield diminishing returns.

F Evaluation Protocols and Prompt Templates

F.1 Evaluation Benchmarks and Metrics

We evaluate all models under the same zero-shot setting. For mathematical reasoning, we use MathVista, MathVision, MathVerse, WeMath, LogicVista, and ChartQA. For vision-centric understanding, we use MMMU, MMVP, and BLINK. Unless otherwise noted, the average in the main tables is computed as the equally weighted average of the mathematical-reasoning average and the vision-centric average.

F.2 Answer Normalization and Scoring

For rule-based verification, the model response is first parsed into the required answer field. We normalize trivial formatting differences, including surrounding whitespace, capitalization for short textual answers, and common numerical formats. For ChartQA, we follow the official relaxed numerical accuracy protocol when reporting ChartQA-specific accuracy. For other benchmarks, we use each benchmark’s standard answer matching or official evaluation script whenever available.

F.3 Actor Rollout Prompt

The Actor is prompted to solve the visual question and return a response in the required reasoning-and-answer format. The key requirement is that the final answer can be parsed reliably by the verifier.

Actor prompt template. Given the image and the question, reason step by step and provide the final answer in the required format. Put the final answer inside `<answer>` and `</answer>`. The answer should be concise and directly match the question.

F.4 EnvRewriter Prompt

The EnvRewriter is prompted to modify the visual environment while preserving verifiability. For structured domains, it must output an executable edit command over the scene graph or data table. For natural-image VQA, it must avoid changing the protected answer-relevant region.

EnvRewriter prompt template. You are an environment rewriter. Given the original image metadata, question, answer, current Actor pass rate, and available edit tools, propose one valid edit that adjusts task difficulty toward the learnable zone. Return a structured command with the fields `tool`, `params`, and `reasoning`. The edit must remain executable and must preserve or programmatically update the answer.

F.5 Evaluation Prompt

During evaluation, we use a deterministic prompt format and do not expose the model to EnvRewriter metadata, pass-rate statistics, or training-time edit commands. The model only receives the test image and question.

Evaluation prompt template. Answer the question based on the image. Provide the final answer in `<answer>` and `</answer>`. Do not include any information that is not supported by the image.

F.6 Baseline Implementation Details

We compare against three categories of baselines: RLVR-trained reasoning models, self-evolution methods, and co-evolution methods that do not edit the visual environment. For published baselines, we use reported numbers when available under comparable settings. For in-house ablations, including Direct GRPO, Supervised GRPO, text-only editing, and static offline augmentation, we use the same Actor backbone and the same evaluation protocol as VICO to isolate the effect of visual-environment co-evolution.

F.7 Full ChartQA EnvRewriter Prompt

```
You are an expert chart editing planner.

Goal: choose one edit that moves the Actor pass rate ( $\hat{p}$ ) closer to 0.5.

Tool:
- chart_rerender(edit_instruction): edit the chart's underlying data table and
  re-render it with matplotlib.

Rules:
- To make harder: add near-miss distractors, change the answer value, or increase
  chart density.
- To make easier: remove distractors, simplify the chart, or make the answer
  more distinct.
- Return one specific executable edit.

Output format:
<think>
your reasoning
</think>
<tool_call>
{"tool": "chart_rerender", "params": {"edit_instruction": "your edit"}}
</tool_call>
```

Listing 1: rewriter editing planner prompt.

G Additional Main Results

G.1 Full OOD Average Calculation

For the Chart-domain variant, we report the out-of-distribution average by excluding ChartQA, because ChartQA is the in-domain visual source for that variant. This avoids overstating generalization by including the benchmark most directly aligned with the training domain. For CLEVR and ZwZ variants, the same benchmark list is kept for consistency in the main comparison.

G.2 Cross-Backbone Results

VICO improves across different VLM backbones, suggesting that the co-evolution loop is not specific to a single model family.

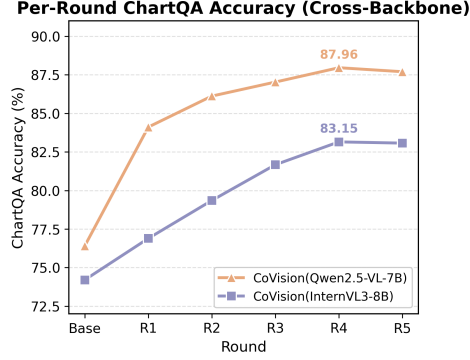


Figure 11: **VICO improves accuracy across VLM backbones.** Per-round ChartQA accuracy rises for both tested models, showing that the emergent curriculum is not tied to one model family.

Table 14: **VICO cuts labeling cost while staying competitive.** Label Cost counts teacher or judging LLM tokens with the Qwen2.5 tokenizer. Programmatic-label methods, including VICO, use no LLM labeling tokens; baseline training costs are estimated from reported RL samples, while VICO cost is directly measured.

Method	Data Cost			Training			Performance	
	Prepare Method	Num (RL)	Label Cost (Tokens)	Method	Interact	Time Cost	MathVerse	Mathvista
Qwen2.5-VL-7B	—	—	—	—	—	—	39.6	68.2
R1-OneVision-7B	Programmatic + human checks	10k	≥ 1.1 M	SFT+GRPO	✗	≥ 170 A100-Hours	46.4	64.1
VLAA-Thinker-7B	Teacher LLM-generated traces	25k	29.6 M	SFT+GRPO	✗	≥ 120 A100-Hours	48.2	68.0
OpenVLThinker-7B	Teacher LLM-generated solutions	9k	5.7 M	SFT+GRPO	✗	≥ 125 A100-Hours	47.9	70.2
MM-Eureka-Qwen-7B	Human-curated	15k	—	GRPO	✗	≈ 700 A100-Hours	50.3	73.0
ViGaL-Snake	Game environment via PPO	72k	0	RLOO	✗	≈ 170 A100-Hours	51.1	70.7
ViGaL-Rotation	Game environment via PPO	72k	0	RLOO	✗	≈ 170 A100-Hours	50.4	71.2
VICO-Qwen2.5VL-7B(Chart)	Co-evolutionary editing	2000	0	Co-evolve+GRPO	✓	≈ 149 A100-Hours	54.9	72.8

G.3 Cost and Annotation Efficiency

We provide a transparent accounting of VICO’s computational and annotation costs to facilitate reproducibility and position the method against existing chart-specialized approaches.

Definition of label cost. We define “labeled QA pairs” as human-annotated or strong-LLM-generated question-answer pairs used as supervision targets during training. VICO uses seed images from existing public collections but does not require additional human-written (q, a) pairs during co-evolution: the EnvRewriter modifies a structured representation of each image, and the corresponding (q', a') pair is computed programmatically from the modified representation. The seed images themselves are inputs to the loop and do not require new human labels.

Compute budget. We report the measured cost for the VICO-Qwen2.5-VL-7B chart-backbone setting, which requires approximately 149 A100 GPU hours. For the main Qwen3VL-8B setting, the full VICO pipeline runs through R5 for saturation analysis. The actor-training stage through R4 requires approximately 305 A100 GPU hours: ~ 101 for Round 1, ~ 85 for Round 2, ~ 27 for Round 3, and ~ 91 for Round 4, which trains for more steps. The R5 run is used to verify saturation. Trajectory generation contributes an additional ~ 40 A100 GPU hours and is parallelizable across rounds.

No additional human annotation during training. Each edited training pair is derived from the EnvRewriter’s modified structured representation, eliminating the need for human-labeled (q, a) pairs at any stage of the co-evolution process.

G.4 Comparison with Chart-Specialized Methods

Table 15 compares VICO against three recent chart-specialized methods: Chart-R1 [7], Bespoke-MiniChart-7B [28], and ECD [46]. VICO-Qwen3VL-8B reaches 89.12% on ChartQA using seed visual inputs and no additional labeled QA pairs, while remaining competitive with methods that use tens or hundreds of thousands of labeled pairs.

1. *Strong cost-efficiency:* VICO avoids additional labeled QA supervision and uses substantially fewer seed inputs than chart-specialized SFT/RL approaches.

Table 15: **VICO reaches competitive ChartQA accuracy with far fewer labeled QA pairs.** All methods use ChartQA’s official relaxed accuracy with 5% numerical tolerance. VICO uses seed inputs and avoids extra labeled QA supervision, while chart-specialized baselines require tens or hundreds of thousands of labeled pairs.

Method	Labeled QA	ChartQA (%)
Chart-R1-7B [7]	~33k	91.04
Bespoke-MiniChart-7B [28]	~91k	89.5
ECD (Qwen2.5-VL-7B) [46]	~320k	85.32
VICO-Qwen2.5-VL-7B (Ours)	2,000 seed inputs	87.96
VICO-Qwen3-VL-8B (Ours)	2,000 seed inputs	89.12

2. *Practical paradigm:* VICO scales to new domains without proportional annotation effort, making it attractive in domains where labeled QA is scarce.

G.5 Additional Per-Benchmark Results

Extended per-benchmark details are reported in the domain-specific tables and analyzes throughout this appendix.

H Ablation and Robustness Studies

H.1 EnvRewriter SFT as a Co-evolution Catalyst

We examine the relationship between supervised initialization and co-evolution using four experimental settings (Table 6). The EnvRewriter is initialized on verified GPT-5 edit demonstrations, which supervise both executable command generation and difficulty-adjustment strategies. These comparisons assess the benefit of combining this initialization with co-evolution.

Direct Actor SFT baseline. Applying supervised fine-tuning directly to the Actor, without co-evolution, improves ChartQA from 76.9% to 79.4%, a gain of 2.5 percentage points. This comparison measures the effect of direct Actor SFT in the evaluated setting; it does not isolate the contribution of the GPT-5 demonstrations used to initialize the EnvRewriter.

Co-evolution without EnvRewriter SFT. Running the co-evolution loop with a vanilla, non-SFT EnvRewriter reaches 78.6% (1.7 percentage points above the base model). On manual inspection, the vanilla EnvRewriter frequently produces malformed or unexecutable edit commands, limiting the supply of valid training samples. This result highlights the importance of initializing an EnvRewriter that can produce executable edits.

Combining EnvRewriter SFT and co-evolution. Initializing the EnvRewriter with verified GPT-5 edit demonstrations and then updating it through co-evolution yields 89.1% on ChartQA (12.2 percentage points above the base model). The combined setting outperforms both direct Actor SFT and co-evolution with a non-SFT EnvRewriter, supporting the complementary roles of supervised initialization and iterative actor–environment adaptation.

These results support combining EnvRewriter SFT with co-evolution. Because the initialization demonstrations supervise both command format and editing strategy, the present comparisons do not separately quantify these two contributions or isolate the contribution of GPT-5-generated supervision.

H.2 Static Offline Augmentation Details

To test whether the gain comes simply from stronger generated data, we compare VICO against static offline augmentation without the iterative actor–environment loop. The offline variants generate a fixed corpus with self-generation, GPT-5, or Nano Banana, and then train the Actor on that fixed data. These variants improve over the base model but remain below iterative visual co-evolution, showing that the dynamic feedback loop contributes more than one-shot data quality.

H.3 Text-Only Editing vs. Visual Editing

To isolate the role of the editing modality, we compare text-only perturbation with visual editing under the same CLEVR training source. Text-only perturbation changes the question or answer format while keeping the visual scene fixed. Visual editing modifies the image itself through the verifiable editing pipeline. The main results show that visual editing provides larger gains, especially on chart reasoning, supporting the claim that effective multimodal co-evolution requires adapting the visual environment rather than only rewriting text.

H.4 Robustness to Imperfect Image Editing

In practice, image editors may produce failures such as blank renders or mismatches between images and labels. To simulate partial editing failures, we corrupt 20% of the R1 training data: 10% of the samples are replaced with blank white images, and another 10% use unedited original images paired with edited labels. As shown in Table 7, the overall average performance drops only marginally from 66.8% to 66.0%, less than one point, and the noisy model still outperforms the base model by +2.4%. This shows that VICO does not rely on a perfect image editor: failed edits do not fully destroy the training signal, and the remaining valid samples still support stable co-evolution.

H.5 Stability Across Random Seeds

A natural concern for any RL-based training pipeline is whether the reported gains depend on a favorable random seed. We re-ran the first round of training with three independent random seeds on CLEVR and evaluated the resulting VICO-8B (CLEVR) checkpoints on ChartQA and MathVista.

Table 16: **VICO is stable across random seeds.** We re-run the first CLEVR training round with three seeds and evaluate on ChartQA and MathVista. Standard deviation is far below the reported gains, so improvements are not driven by favorable seed selection.

Seed	ChartQA (%)	MathVista (%)
Seed 1 (reported)	85.2	73.8
Seed 2	84.5	72.9
Seed 3	85.2	71.7
Mean $\pm$ Std	85.0 $\pm$ 0.4	72.8 $\pm$ 1.1
Base (Qwen3VL-8B)	76.9	67.7
Gain over base	+8.1	+5.1

We focus this analysis on Round 1 because in VICO, the seed data distribution is fixed once the first round is initialized; subsequent rounds operate on EnvRewriter-generated samples that no longer depend on the initial seed. As shown in Table 16, the standard deviation of final accuracy is 0.4 points on ChartQA and 1.1 points on MathVista, well within the margin of our reported improvements. We therefore report single-seed results in the main text, following the convention adopted by prior self-evolution and co-evolution work.

H.6 Robustness to Initial Data Difficulty

A second source of variability is the initial task difficulty. Fixed-distribution methods can be sensitive to this choice: easy seeds leave little room for improvement, while hard seeds can stall training.

VICO is less sensitive by design. The EnvRewriter is rewarded for producing edits with a pass rate near $\alpha = 0.5$. It makes easy samples harder and hard samples easier, pushing both toward the sweet zone. As shown in Appendix I.1, pass rates converge from both directions, suggesting that VICO’s gains come from the co-evolution loop rather than a specially curated initial difficulty distribution.

Table 17: **The EnvRewriter moves both strong and weak Actors toward the sweet zone.** On ChartQA, it lowers the pass rate of a strong Actor; on ZwZ, it raises the pass rate of a weak Actor. Both converge toward $[0.35, 0.65]$, showing actor-relative difficulty calibration.

Round	n	$\hat{p}_{\text{orig}}$	$\hat{p}_{\text{final}}$	Editing Intensity
<i>ChartQA (strong Actor $\rightarrow$ EnvRewriter pushes down)</i>				
R1	2200	0.846	0.622	+0.225
R2	2200	0.829	0.502	+0.328
R3	2200	0.822	0.502	+0.321
R4	2200	0.848	0.387	+0.461
R5	2200	0.889	0.375	+0.514
<i>ZwZ (weak Actor $\rightarrow$ EnvRewriter pulls up)</i>				
R1	2000	0.209	0.651	−0.442
R2	2000	0.229	0.583	−0.354
R3	2000	0.223	0.524	−0.301
R4	2000	0.231	0.433	−0.203
R5	2000	0.227	0.442	−0.215

I Co-Evolution Dynamics and Qualitative Analysis

I.1 Bidirectional Difficulty Calibration

The EnvRewriter calibrates difficulty from both directions. On ChartQA, the initial Actor is strong, so the EnvRewriter lowers the pass rate toward the sweet zone. On ZwZ, the initial Actor is weak, so the EnvRewriter raises the pass rate toward the sweet zone. This supports the claim that VICO performs actor-relative calibration rather than random perturbation.

I.2 Editing Intensity and Response Length

We further find that editing intensity and output length evolve differently. As reported in Table 18 and Figure 12(a), editing intensity increases from 0.22 to 0.51 across rounds, while the average EnvRewriter instruction length remains almost constant ($973 \rightarrow 981$ characters). This suggests that the EnvRewriter learns to apply stronger and more targeted edits without producing longer instructions. In contrast, the Actor’s response length grows from 811 to 1207 characters (+49%), indicating longer reasoning chains as the tasks become more challenging. Together, these trends highlight a clear co-evolutionary process: the EnvRewriter poses increasingly well-calibrated challenges, and the Actor correspondingly develops more elaborate reasoning to tackle them.

Table 18: **Editing intensity grows without longer EnvRewriter instructions.** Across rounds, edits become stronger while instruction length stays nearly fixed; Actor responses grow as tasks become harder.

Metric	Early round	Late round	Change
Editing intensity $ \hat{p}_{\text{orig}} - \hat{p} $	0.22	0.51	+125%
EnvRewriter instruction length	973	981	+0.8%
Actor response length	811	1207	+49%

This co-adaptation has limits. Figure 12(b,c) shows that the per-round accuracy improvement declines from +8.34% to −0.18%, and the sweet-zone hit rate falls from 53.4% to 11.1%. These patterns indicate that, over time, the EnvRewriter struggles to keep up with the Actor’s capacity ceiling. We analyze this saturation phenomenon theoretically in Appendix E.6.

I.3 Sample-Level Flip Analysis

To understand the Round 4 gain, we compare sample-level correctness across the base model and R1–R4 Actors on the ChartQA test set. Wrong-to-correct flips dominate correct-to-wrong regressions, showing that the gain reflects broad capability improvement rather than error redistribution. Most

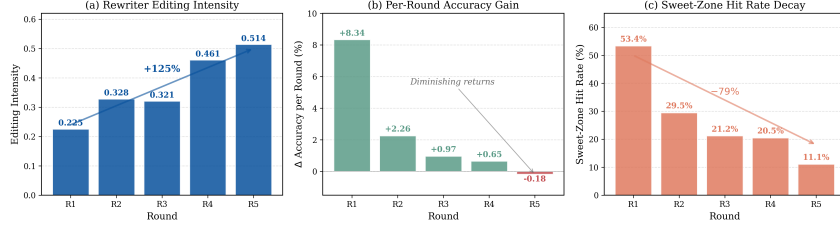


Figure 12: **Saturation appears near the Actor’s capacity ceiling.** Editing intensity grows by +125%, per-round gains shrink from +8.34% to −0.18%, and sweet-zone hit rate falls from 53.4% to 11.1%, matching Eq. E.6.

Table 19: **Positive capability flips dominate regressions.** On ChartQA, wrong-to-correct flips from Base to R4 outnumber correct-to-wrong flips by 5.7×1 , showing that VICO improves capability rather than merely moving errors across samples.

Outcome	n	%
Both correct (Base ✓, R4 ✓)	1863	74.5
Improvement (Base ✗ → R4 ✓)	365	14.6
Regression (Base ✓ → R4 ✗)	64	2.6
Both wrong (Base ✗, R4 ✗)	208	8.3

newly solved samples unlock early and remain stable, with stable correctness and R1 unlocks covering the largest fraction of cases.

I.4 Question-Type Breakdown

The main text shows that gains concentrate on reasoning-heavy ChartQA question types, such as ratio/percentage, value lookup, and difference. These categories require multi-step reading and computation, so their larger improvements support the claim that VICO improves visual reasoning rather than simply increasing recognition accuracy on easy cases.

I.5 Chain-of-Thought Case Studies

Setup. Starting from Qwen3VL-8B-Instruct (76.9% on ChartQA test), we run four rounds of VICO. In each round, the EnvRewriter generates approximately 2,000–3,000 modified training images; the Actor is trained via GRPO on these images together with a fixed regularization set of 2,000 original ChartQA samples; and the resulting Actor checkpoint serves as the starting point for the next round.

CoT case analysis. Representative cases show that the base model tends to produce direct, single-step answers that miss key constraints, whereas the trained model exhibits explicit step-by-step decomposition, such as identifying relevant chart regions, reading the y-axis, and computing the final answer. Manual inspection of 20 randomly sampled base-wrong → R4-correct pairs confirms this pattern is systematic.

J Preliminary Experiments on Difficulty-Aware Visual Editing

These preliminary experiments explored how to construct visual edits whose difficulty is calibrated to an Actor. They informed the final design but used different generation and optimization procedures from the main experiments. In particular, the online Rewriter GRPO experiments described below are distinct from the final EnvRewriter SFT initialization and RWR updates.

Early image-editing pipeline. We first explored a pipeline in which a Rewriter proposed a natural-language perturbation plan and an external image generator executed it while attempting to preserve the original question and answer. Scene analysis and object segmentation provided additional editing context. The Actor then answered the edited question repeatedly to estimate its pass rate, and the resulting difficulty signal was used to update the Rewriter with online GRPO. Although the generated images could shift aggregate task difficulty, these runs did not show stable calibration toward the

Table 20: **Most new ChartQA capabilities unlock early and remain stable.** Each sample is represented by a 5-bit correctness sequence across Base and R1–R4. The top panel shows first-correct rounds; the bottom lists common trajectories. The top five patterns cover 92.5% of samples, led by stable correctness (11111) and stable R1 unlocks (01111).

State	n	%	Pattern	n	%
Already correct at Base	1927	77.1	11111	1796	71.8
Newly unlocked at R1	347	13.9	01111	306	12.2
Newly unlocked at R2	37	1.5	00000	171	6.8
Newly unlocked at R3	15	0.6	10111	22	0.9
Newly unlocked at R4	3	0.1	10000	18	0.7
Persistent failures	171	6.8			
Mutually exclusive sum	2500	100.0	<i>Top 5</i>	2313	92.5
			<i>Other 26 patterns</i>	187	7.5
Non-monotonic (any regression)	197	7.9	Total	2500	100.0

target pass rate. Edited samples frequently remained either too easy or too hard, leaving relatively few samples at intermediate difficulty.

Answer matching and prompt consistency. Offline diagnosis exposed scoring errors that could obscure the effect of an edit. Substring matching could incorrectly accept a prediction containing the answer as part of a different value, while overly strict matching of an entire response could reject a correct answer embedded in explanatory text. For multiple-choice questions, omitting the choices from the Actor prompt also created a mismatch between free-form predictions and option-letter labels. Providing the complete choices and explicitly parsing the final option corrected these mismatches. This diagnosis motivated consistent answer extraction and normalization, with numerical precision and units aligned to the question’s requirements. The scoring protocol used in the final experiments is described in Appendix F.2.

Calibration requires distribution-level diagnostics. The mean pass rate alone did not adequately characterize generation quality. A mixture of samples with pass rates near zero and one can have a mean near 0.5 without producing intermediate-difficulty samples. We therefore distinguish the pass rate of an individual edited sample, its average across samples, and the fraction of samples in the target band. Difficulty statistics must also identify whether their denominator includes failed or invalid generations. Repeated sampling yields a finite-resolution estimate of success probability; an observed pass rate is consequently an empirical measurement under a specific Actor and sampling configuration, rather than an exact difficulty label.

Reward and optimization observations. We explored both threshold-based rewards and a continuous improvement reward $|\hat{p}_{\text{base}} - 0.5| - |\hat{p}_{\text{edit}} - 0.5|$. The latter measures whether an edit moves the Actor closer to the target. However, when both the original and edited samples have extreme pass rates, their distances to the target are equal and this reward provides no preference between the edits. The recorded runs exhibited limited reward differentiation and did not consistently increase the supply of calibrated samples. These observations concern the tested pipeline and do not establish a general limitation of GRPO. A near-zero reported loss alone is also insufficient to establish that parameter gradients vanish.

Implications for the final design. These experiments motivated separating edit validity from difficulty assessment, using explicit editing interfaces, and training the EnvRewriter on verified edit transitions with measured Actor feedback. The final method uses the domain-specific validity rules in Appendix C and the RWR procedure in Appendix B.3. The preliminary improvement reward and online Rewriter GRPO procedure are not the optimization recipe used for the main results.

K Case Study: Co-Evolution Matters More Than Image-Generation Strength

This case study explains why VICO uses verifiable, actor-conditioned editing: the goal is to adjust difficulty while keeping labels clean.

Why not simple perturbations or unconstrained generation? Noise, blur, and occlusion can lower the Actor’s pass rate, but they mainly add perceptual difficulty, not reasoning difficulty. Unconstrained generation may produce plausible edits, but it can change answer-relevant content, introduce ambiguity, or invalidate labels. Such failures harm RLVR because rewards require reliable verification.

VICO avoids this through explicit validity constraints. CLEVR recomputes answers from edited scene graphs. ChartQA uses a two-tier table rule: Tier 1 recovers a' by entity-anchored lookup, while Tier 2 preserves $a' = a$ by fixing answer-bearing CSV values. ZwZ protects answer-relevant regions and edits only non-target regions.

Strong generators are complementary, not replacements. GPT-5 and Nano Banana can serve as strong editing backends, but they do not replace the actor-conditioned environment policy. Used once, they create a fixed corpus that can saturate, remain too hard, or expose shortcuts. Used inside the loop, they still need a policy to select valid edits and target the learnable zone. Thus, the key factor is dynamic, verifiable, actor-conditioned co-evolution, not image-generation capability alone.

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Answer: [Yes]

Justification: The paper explicitly describes the use of large vision-language models in the core methodology: the Actor and EnvRewriter are initialized from VLM backbones and are jointly trained in the co-evolution loop. The paper also describes the use of GPT-5 and Gemini (Nano Banana) as stronger offline augmentation baselines, and reports the model backbones, prompts, reward functions, and training settings used in the experiments.

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