# *VisPlay*: Self-Evolving Vision-Language Models from Images

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## Abstract

*Reinforcement learning (RL) provides a principled framework for improving Vision-Language Models (VLMs) on complex reasoning tasks. However, existing RL approaches often depend on human-annotated labels or task-specific heuristics to define verifiable rewards—both costly and limited in scalability. We introduce VisPlay, a self-evolving RL framework that enables VLMs to autonomously improve their reasoning capabilities from massive unlabeled image data. Starting from a single base VLM, VisPlay assigns the model into two interacting roles: an **Image-Conditioned Questioner** that formulates challenging yet answerable visual questions, and a **Multimodal Reasoner** that generates silver responses. These roles are jointly trained using Group Relative Policy Optimization (GRPO), which uses diversity and difficulty rewards to balance the difficulty of generated questions with the quality of silver answers. VisPlay scales efficiently across two model families. Trained on Qwen2.5-VL and MiMo-VL, VisPlay achieves consistent improvements in visual reasoning, compositional generalization, and hallucination reduction across eight benchmarks including MM-Vet and MMMU, and establishes a scalable path toward self-evolving multimodal intelligence. Our project page is available at https://bruno686.github.io/VisPlay/.*

## 1. Introduction

Self-evolving mechanisms [8, 32] represent a promising frontier for advancing artificial intelligence. The training of state-of-the-art (SoTA) models has traditionally relied on large volumes of expert curated tasks and labels. However, the reliance on human annotation is not only costly, labor-intensive, and difficult to scale, but also presents a funda-
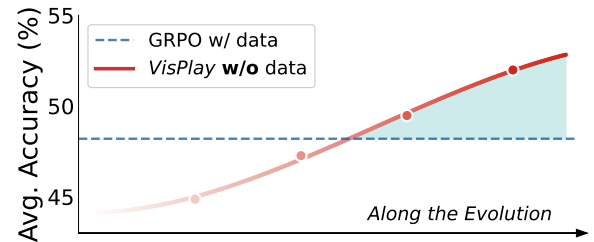


Figure 1. Illustration of the average accuracy improvement (averaged over seven datasets) through successive evolutions (Evo 1 to Evo 5) on Qwen2.5-VL-3B-Instruct, compared to a baseline trained on Vision-47K with GRPO, demonstrating the effectiveness of our *VisPlay* .

mental bottleneck to advancing intelligence toward capabilities that could surpass itself without human signal guidance [45]. Self-evolution offers a compelling alternative by equipping models with the capacity to independently generate, refine, and learn from their own experiences such as through self-play or synthetic data generation.

Motivated by these advantages, the research community has increasingly explored self-evolution, most notably in the context of Large Language Models (LLMs). A line of works have demonstrated how LLMs can autonomously enhance their complex reasoning and coding faculties, often by generating their own tasks or data [16, 26, 51]. However, the self-evolution paradigm remains largely underexplored for Vision-Language Models (VLMs) [2, 22, 35]. Unlike LLMs, which rely solely on text, developing self-evolving VLMs poses additional challenges due to their dependence on the visual modality. In a world where human annotation is costly and time-consuming, yet vast amounts of visual data are freely available online, self-evolving VLMs present a promising direction to continual improvement without human signals and directly from the abundant visual content on the internet [3, 33].

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*Core Contribution.

In this paper, we introduce *VisPlay*, a self-evolving RL framework that enables VLMs to autonomously improve their reasoning capabilities using **only raw, unannotated images**. The framework utilizes a single base VLM that alternates between two roles: the *Image-Conditioned Questioner*, which generates diverse and challenging questions conditioned on an input image, and the *Multimodal Reasoner*, which produces silver responses based on both the image and the generated question. Both roles are jointly optimized using Group Relative Policy Optimization (GRPO) [34], where designed rewards encourage a balance between question difficulty and answer quality without requiring external supervision. The Image-Conditioned Questioner learns to generate challenging yet answerable questions grounded in visual inputs, while the Multimodal Reasoner learns to produce accurate, detailed, and grounded responses. This self-evolving framework enables the VLM to progressively improve its visual reasoning abilities through iterative co-improvement of the Questioner and the Reasoner as Figure 1.

We apply our self-evolving RL framework to train three state-of-the-art (SoTA) VLMs and observe consistent performance gains across diverse visual reasoning benchmarks.

Our main contributions are:
- We propose *VisPlay*, a self-evolving RL framework for Vision-Language models.
- We apply *VisPlay* to three strong models—Qwen2.5-VL-3B, Qwen2.5-VL-7B [35], and MiMo-VL-7B [43]. We run extensive evaluations over three major domains—General Visual Understanding, Visual Mathematics, and Hallucination Detection. All models show consistent gains in accuracy after several iterations.
- We run extensive ablation studies to further validate the contribution of Image-Conditioned Questioner and the Multimodal Reasoner component to further show how *VisPlay* progressively strengthens multimodal reasoning across vision-language tasks.

## 2. Method

### 2.1. Preliminary

Reinforcement Learning with Verifiable Rewards (RLVR) [20] is a paradigm for training VLMs in domains where the correctness of model outputs can be verified. A rule-based verifier $v : X \rightarrow \{0, 1\}$ assigns a binary reward to each generation $x_i$:

$$r_i = v(x_i) = \begin{cases} 1, & \text{if } x_i \text{ satisfies a correctness rule,} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Such verifiable rewards are effective in tasks like mathematical reasoning, multiple choice, and code genera-

tion [52], where correctness can be objectively evaluated. GRPO [34] provides a practical RL algorithm without a value function by using relative rewards among multiple samples from the same prompt. Given a prompt $p$, a policy $\pi_{\theta_{\text{old}}}$ produces $G$ complete responses $\{x_1, \ldots, x_G\}$ with corresponding rewards $\{r_1, \ldots, r_G\}$. Rewards are normalized within the group to compute response-level advantages:

$$\hat{A}_i = \frac{r_i - \text{mean}(r_1, \ldots, r_G)}{\text{std}(r_1, \ldots, r_G) + \varepsilon_{\text{norm}}}, \quad (2)$$

where $\varepsilon_{\text{norm}}$ is a small constant for stability.

The policy is then optimized using a clipped surrogate objective, regularized by a KL term to constrain policy drift:

$$\begin{aligned} \mathcal{L}_{\text{GRPO}}(\theta) = -\frac{1}{G} \sum_{i=1}^{G} \min\Bigg( &\frac{\pi_\theta(x_i)}{\pi_{\theta_{\text{old}}}(x_i)} \hat{A}_i, \\ &\text{clip}\left( \frac{\pi_\theta(x_i)}{\pi_{\theta_{\text{old}}}(x_i)}, 1-\epsilon,\, 1+\epsilon \right) \hat{A}_i \Bigg) \\ &+ \beta\, \text{KL}(\pi_\theta \,\|\, \pi_{\theta_{\text{old}}}). \end{aligned} \quad (3)$$

GRPO operationalizes RLVR principles to improve reasoning and generation quality in VLMs by rewarding responses with positive relative advantages while limiting policy deviation

### 2.2. Pipeline Overview

We introduce *VisPlay*, a self-play reinforcement learning framework designed to evolve VLMs without human-annotated data. As illustrated in Figure 2, the framework operates as a closed-loop system involving two agents evolved from the same base model: an *Image-Conditioned Questioner* and a *Multimodal Reasoner*. The process begins with the Questioner taking an image as input to generate a visual query. Subsequently, the Reasoner receives both the image and the generated query to produce a response. Both the Questioner and the Reasoner are initialized from a shared pretrained backbone. The two agents co-evolve through iterative interactions: the Questioner is trained to generate more challenging questions, while the reasoner is trained to solve more and more challenging questions. The complete process is described in Algorithm 1.

### 2.3. Image-Conditioned Questioner Training

The Questioner is an autoregressive policy denoted by $Q_\theta$. Conditioned on an input image $I$, it samples a group of $G$ questions $\{x_i\}_{i=1}^{G} \sim Q_\theta(\cdot | I)$, which are evaluated to produce scalar rewards $\{r_i\}_{i=1}^{G}$. These rewards are used to compute group-normalized advantages and to update $Q_\theta$ with a GRPO objective. We next define reward components that constitute each $r_i$.
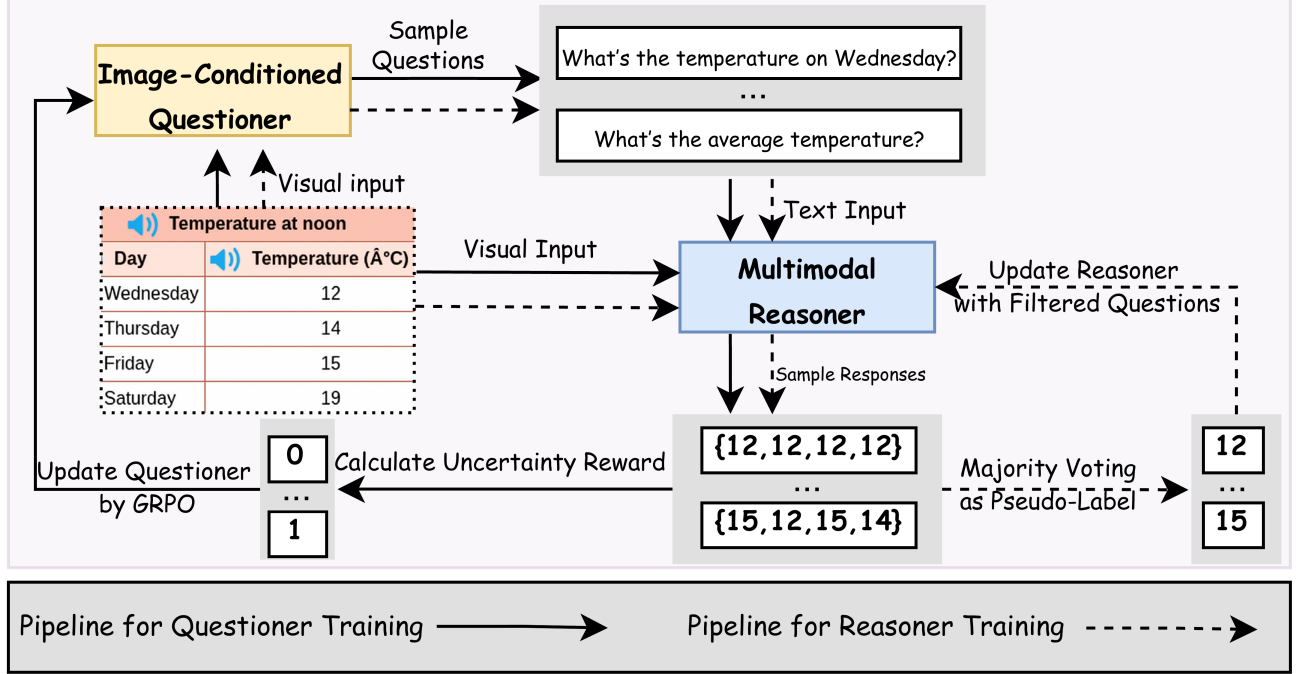
Figure 2. An illustration of our *VisPlay* framework, depicting the co-evolution of the Image-Conditioned Questioner and Multimodal Reasoner. Top: During the Questioner training stage, the Image-Conditioned Questioner is optimized via GRPO to produce challenge questions. The reward stems from the uncertainty of the frozen Multimodal Reasoner, computed by the consistency of its multiple generated answers. Bottom: In the Reasoner training stage, the Multimodal Reasoner is trained via GRPO on a curated set of challenging questions from the now-frozen Image-Conditioned Questioner, leveraging pseudo-labels from its own majority voting.

**Pseudo-Label Generation.** Since self-evolving VLMs learn without relying on labeled data, ground-truth answers for the Questioner's generated questions are unavailable. Therefore, we introduce a method to approximate the corresponding answers. Given an image $I$ and the generated question $x$, we introduce a Reasoner $S_\phi$ that samples $m$ responses $\{y_j\}_{j=1}^{m}$.[1] We define the empirical frequency of a candidate answer $y$ as $\hat{p}(y|x,I) = \frac{1}{m}\sum_{j=1}^{m}\mathbb{1}\{y_j = y\}$, and derive the pseudo-label via majority voting [15]: $\tilde{y} = \arg\max_y \hat{p}(y|x,I)$. We then define the **confidence score** for this pseudo-label as:

$$\text{conf}(x,I) = \hat{p}(\tilde{y}|x,I). \tag{4}$$

Intuitively, $\text{conf}(x,I)$ measures the Reasoner's certainty about the pseudo-label: high values indicate stable and consistent predictions, whereas values near 0.5 reflect strong uncertainty. We therefore treat the degree of uncertainty (i.e., how close $\text{conf}(x,I)$ is to 0.5) as a proxy for the model-perceived difficulty of the generated question.

**Uncertainty Reward.** The confidence score quantifies the Reasoner's uncertainty, which we use as a proxy for the model-perceived difficulty of the generated question. To encourage questions that probe the Reasoner's limits, we compute the reward based on the confidence score $c = \text{conf}(x,I)$. We define the uncertainty reward to penalize deviations from the point of maximum uncertainty:

$$r_{\text{unc}}(x,I) = 1 - |2c - 1|. \tag{5}$$

This formulation yields a maximal reward of 1 when $c = 0.5$ and decreases linearly to 0 as the reasoner's response distribution becomes deterministic (i.e., $c \to 1$).

**Diversity Regularization.** To prevent the model from collapsing [5, 6, 9, 28, 54] into generating repetitive questions for a given image $I$, we introduce a redundancy penalty within its generated group $\mathcal{X}_I$. We cluster these generated questions based on pairwise similarity (BLEU score) to identify duplicates. For a question $x_i$ belonging to a cluster $C_k^{(I)} \subseteq \mathcal{X}_I$, the regularization term is:

$$r_{\text{div}}(x_i, I) = \lambda \frac{|C_k^{(I)}|}{G}, \tag{6}$$

where $C_k^{(I)}$ denotes the cluster of similar questions for image $I$, and $G$ is the total number of generated questions for that image.

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[1]The reasoner is evolved from the same base model as the Questioner. See Section 2.4 for details.

**Format constraint.** We enforce a hard filter to ensure structural validity. Specifically, we require the generated question to be strictly enclosed within `<question>` tags. Any output failing to meet this format requirement is assigned zero reward. We denote this validity indicator as:

$$\mathbb{1}_{\text{valid}}(x) = \begin{cases} 1, & \text{if } x \text{ is wrapped in } \texttt{<question>} \text{ tags,} \\ 0, & \text{otherwise.} \end{cases}$$
$$(7)$$

**Final Questioner Reward.** For each generated question $x_i$ conditioned on image $I$, we integrate the uncertainty signal and diversity regularization into a unified scalar objective:

$$r_i = \mathbb{1}_{\text{valid}}(x_i) \cdot \text{ReLU}\Big(r_{\text{unc}}(x_i, I) - r_{\text{div}}(x_i, I)\Big). \quad (8)$$

This composite reward incentivizes the Questioner to generate challenging yet non-redundant questions while strictly filtering out malformed outputs. The ReLU function stabilizes GRPO updates by preventing spurious negative values from skewing the reward normalization across the group.

## 2.4. Multimodal Reasoner Training

The training of the Multimodal Reasoner $S_\phi$ builds upon the advancements of the Image-Conditioned Questioner. In each iteration, the Image-Conditioned Questioner functions produce challenging samples that serve as training targets. The Multimodal Reasoner then learns from these automatically curated samples, improving its visual reasoning ability without any external supervision.

**Curated Dataset Construction.** Following the update of the Image-Conditioned Questioner, we generate a diverse pool of $N$ candidate questions $\{x_i\}_{i=1}^N$ per image by sampling $x_i \sim Q_\theta(\cdot \mid I)$. For each $x_i$, we obtain $m$ response samples from the current Multimodal Reasoner and compute the pseudo-label $\tilde{y}_i$ and confidence score $c_i = \text{conf}(x_i, I)$. To focus on training samples that offer high information gain, we enforce an *informative filter* that retains pairs $(x_i, \tilde{y}_i)$ with moderate confidence:

$$\tau_{\text{low}} \le c_i \le \tau_{\text{high}}, \quad (9)$$

where $\tau_{\text{low}}$ and $\tau_{\text{high}}$ are thresholds set to 0.25 and 0.75, respectively. This criterion effectively discards trivial samples where the model is already certain ($c_i > 0.75$) as well as highly unstable or noisy generations ($c_i < 0.25$). The final curated training set $S$ is formed by collecting all retained pairs across images, up to a budgeted size, to optimize the Multimodal Reasoner via GRPO.

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**Algorithm 1:** *VisPlay*: Self-Evolving RL for Vision-Language Models

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**Input:** Initial models $Q_\theta, S_\phi$; Image dataset $\mathcal{I}$; Group size $G$; Reasoner samples $m$; Dataset budget $N$; Thresholds $\tau_{\text{low}} = 0.25, \tau_{\text{high}} = 0.75$.
**Output:** Evolved models $Q_\theta$ and $S_\phi$.

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**1** **for** *each self-play iteration* **do**
**2**    **for** *each image batch* $I \in \mathcal{I}$ **do**
**3**      Sample question group $\{x_i\}_{i=1}^G \sim Q_\theta(\cdot \mid I)$;
**4**      **for** *each question* $x_i$ **do**
**5**        Sample $m$ answers $\{y_j\}_{j=1}^m \sim S_\phi(\cdot \mid I, x_i)$;
**6**        Compute confidence $c_i \leftarrow \text{conf}(x_i, I)$ via majority vote (Eq. 4);
**7**        Compute uncertainty reward $r_{\text{unc}} \leftarrow 1 - |2c_i - 1|$;
**8**        Compute diversity penalty $r_{\text{div}}$ via clustering (Eq. 6);
**9**        Final reward: $r_i \leftarrow \mathbb{1}_{\text{valid}}(x_i) \cdot \text{ReLU}(r_{\text{unc}} - r_{\text{div}})$;
**10**      **end**
**11**      Update $Q_\theta$ via GRPO using rewards $\{r_i\}_{i=1}^G$;
**12**    **end**
**13**    Initialize curated dataset $S \leftarrow \emptyset$;
**14**    **for** *each image* $I \in \mathcal{I}$ **do**
**15**      Generate $N$ candidate questions via $Q_\theta$ ;
**16**      **for** *each candidate* $x_k$ **do**
**17**        Obtain pseudo-label $\tilde{y}_k$ and confidence $c_k$ from $S_\phi$;
**18**        **if** $\tau_{\text{low}} \le c_k \le \tau_{\text{high}}$ **then**
**19**          Add $(I, x_k, \tilde{y}_k)$ to $S$;
**20**        **end**
**21**      **end**
**22**    **end**
**23**    **for** *each minibatch* $(I, x, \tilde{y}) \in S$ **do**
**24**      Sample $G$ answers $\{y_j\}_{j=1}^G \sim S_\phi(\cdot \mid I, x)$;
**25**      Compute binary rewards $r_j \leftarrow \mathbb{1}(y_j = \tilde{y})$;
**26**      Update $S_\phi$ via GRPO using rewards $\{r_j\}_{j=1}^G$;
**27**    **end**
**28** **end**

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**Per-Sample Verifiable Reward.** For a question $x_i \in S$ with pseudo-label $\tilde{y}_i$, the Multimodal Reasoner generates a group of $G$ candidate answers $\{y_j\}_{j=1}^G$. Each sampled answer receives the binary reward

$$r_j = \begin{cases} 1, & \text{if } y_j = \tilde{y}_i, \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

Table 1. Comprehensive results on visual reasoning benchmarks. Each base model is evaluated against two settings: a *VisPlay* (❄ challenger) baseline, in which the Reasoner is trained on questions produced by an untrained Challenger, and our iterative *VisPlay* framework. The highest performance reached during training for each model is emphasized in bold. We take accuracy as the metric.

| Methods | General Visual Understanding | | | | Visual Math | | Hallucination | |
| | MMMU | MM-Vet | RealWorld QA | VisNum Bench | Math Verse | MATH-Vision | Hallusion Bench | Avg. |
|---|---|---|---|---|---|---|---|---|
| *Qwen2.5-VL-3B-Instruct* | | | | | | | | |
| Base Model | 19.95 | 36.24 | 49.28 | 27.08 | 26.14 | 20.23 | 32.81 | 30.61 |
| *VisPlay* (❄ challenger) | 23.34 | 43.58 | 57.78 | 29.33 | 33.50 | 23.39 | 64.88 | 33.77 |
| *VisPlay* (Iter 1) | 29.40 | **48.62** | 67.06 | 30.01 | 29.67 | 22.57 | 91.80 | 44.16 |
| *VisPlay* (Iter 2) | 33.37 | 44.50 | 65.62 | 29.64 | 32.36 | 24.67 | **94.95** | 44.87 |
| *VisPlay* (Iter 3) | **37.11** | 38.07 | **71.90** | **39.15** | **35.15** | **29.97** | 90.54 | **47.27** |
| *Qwen2.5-VL-7B-Instruct* | | | | | | | | |
| Base Model | 23.10 | 44.95 | 57.52 | 32.57 | 33.78 | 24.05 | 66.88 | 40.41 |
| *VisPlay* (❄ challenger) | 35.24 | 45.87 | 69.67 | 32.41 | 35.13 | 26.22 | 78.13 | 38.33 |
| *VisPlay* (Iter 1) | 28.94 | 46.33 | 62.61 | 28.65 | 33.88 | 26.91 | 80.34 | 44.53 |
| *VisPlay* (Iter 2) | 27.07 | 42.66 | 60.92 | 27.08 | 36.32 | 25.00 | 67.72 | 40.97 |
| *VisPlay* (Iter 3) | **38.27** | **46.33** | **69.67** | **32.57** | **39.14** | **31.15** | **92.32** | **48.61** |
| *MiMo-VL-7B-SFT* | | | | | | | | |
| Base Model | 30.22 | **59.17** | 78.17 | 44.80 | 41.80 | 25.33 | 87.17 | 43.56 |
| *VisPlay* (❄ challenger) | 27.54 | 58.72 | 63.27 | 49.66 | 38.78 | 24.80 | 57.83 | 39.63 |
| *VisPlay* (Iter 1) | 25.67 | 56.42 | 69.54 | 51.59 | 40.20 | 25.13 | **87.59** | 43.16 |
| *VisPlay* (Iter 2) | **34.07** | 55.96 | **78.69** | 51.18 | 41.65 | 28.45 | 86.65 | 45.58 |
| *VisPlay* (Iter 3) | 28.24 | 56.88 | 71.50 | **52.69** | **46.02** | **29.44** | 74.55 | **45.69** |

These rewards are group-normalized to produce advantages $\hat{A}_j$ as in Eq. 2 (with the Reasoner's rewards), and $S_\phi$ is updated by minimizing $\mathcal{L}_{\mathrm{GRPO}}(\phi)$ as in Eq. 3.

## 3. Experiments

### 3.1. Benchmarks and Evaluation Protocol

We use existing image datasets from Vision-47K [12, 25], which contains 47K web images collected from diverse domains, e.g. including charts, medical images, exams, textbooks, and driving simulations.[2] We train three backbone models using *VisPlay*—Qwen2.5-VL-3B-Instruct, Qwen2.5-VL-7B-Instruct, and Mimo-7B-SFT.[3] We run evaluation across three multimodal domains [25].

- **General Visual Understanding.** We measure performance on four established benchmarks. MM-Vet [47] provides a unified LLM-based score across recognition, OCR, and visual math tasks. MMMU [48] evaluates cross-modal reasoning and subject knowledge through 11.5K college-level, four-choice questions spanning six academic disciplines. RealWorldQA [41] contains roughly 700 real-world images paired with spatially grounded questions. VisNumBench [40] focuses on vi-

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[2]We only use the images without the questions and answers. Details of the dataset breakdowns are in supplement materials.

[3]The detailed training configurations are provided in the supplementary material.

sual number sense, covering around 1.9K questions involving numerical attributes and estimation tasks.
- **Multimodal Mathematical Reasoning.** MathVerse [50] consists of 2.6K diagram-centric questions spanning geometry and functions, provided in multiple visual-text formats. MATH-Vision [37] includes around 3K competition-level problems across 16 subjects and five difficulty tiers.
- **Visual Hallucination Detection.** HallusionBench [14] is used to analyze model errors, distinguishing between language-only hallucinations and visual-illusion errors, with a simple yes/no evaluation format.

### 3.2. Main Results

We use LLM-as-a-judge to assess the correctness of the answers to ensure more robust evaluation [13, 23]. We present the outputs of the Multimodal Reasoner and analyze its reasoning ability progression in Table 1. We summarize the main findings of our experimental results below.

- *VisPlay* **consistently improves overall performance across different models.** All models trained with *VisPlay* consistently surpass both their corresponding base models and the Base Challenger over successive training iterations. Qwen2.5-VL-3B shows a remarkable improvement, with the average score increasing from 30.61 at baseline to 44.16 after the first iteration and reaching 47.27 at the third. Qwen2.5-VL-7B and MiMo-VL-7B
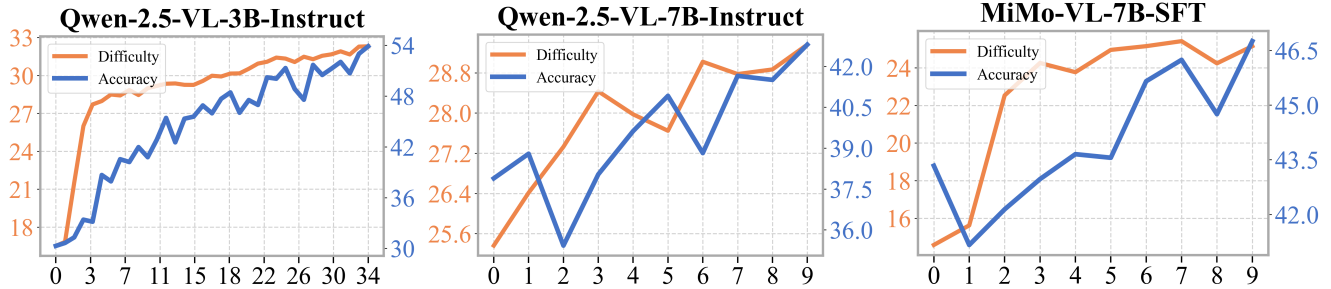
Figure 3. Changes in question difficulty (orange, left axis) and problem-solving accuracy (blue, right axis) during Image-Conditioned Questioner and Multimodal Reasoner training across three VLMs.

Table 2. Analysis of model performance and data quality. The shaded column indicates the estimated accuracy of the self-generated pseudo-labels for each question set, as determined using ChatGLM-Flash.

| | Performance of Evaluated Model (vs. Ground Truth) | | | | |
| --- | --- | --- | --- | --- | --- |
| | Base Model | Reasoner (Iter 1) | Reasoner (Iter 2) | Reasoner (Iter 3) | Pseudo-Label Acc. |
| $\mathcal{D}_{\text{Iter 1}}$ | 39.0 | 44.0 | 45.5 | 49.0 | 72.0 |
| $\mathcal{D}_{\text{Iter 2}}$ | 37.5 | 42.5 | 44.0 | 47.5 | 65.0 |
| $\mathcal{D}_{\text{Iter 3}}$ | 36.0 | 40.0 | 41.5 | 45.0 | 61.0 |

follow similar upward trends, improving from 40.41 to 48.61 and 43.56 to 45.69, respectively. These results demonstrate the robust generalization ability and scalability of the proposed self-evolving framework across different models and model sizes.

- **Performance gains across diverse task types.** *VisPlay* shows improvements across general visual understanding tasks, visual reasoning or math benchmarks, and are more robust to hallucination. For Qwen2.5-VL-3B, the Hallucination score rises from 32.81 to 94.95 by the second iteration, showing a substantial enhancement in factual grounding. Similar patterns are observed in other models—reasoning benchmarks consistently improve without compromising accuracy on general understanding tasks—demonstrating that *VisPlay* effectively strengthens both task-specific reasoning and cross-domain multimodal generalization.

- **Iterative co-evolution between the Questioner and Reasoner drives improvement.** Performance trajectories across iterations highlight the co-evolution between the Questioner and Reasoner. As the Questioner generates more diverse and challenging queries, the Reasoner—trained with GRPO using high-quality silver supervision—learns to handle increasingly complex reasoning steps. This iterative loop allows both components to reinforce each other, leading to continual improvement in reasoning quality, generalization, and robustness. The results indicate that the co-evolutionary design of *VisPlay* provides a scalable path toward self-improving multimodal intelligence.

## 3.3. Performance Comparison with Human-Annotated Data

We conduct a performance comparison between models trained with *VisPlay* and those trained using human-curated image–question–answer pairs from the Vision-47K dataset under standard GRPO for one epoch, as shown in Table 3 for Qwen2.5-VL-3B and 7B. Although this experiment is not an ablation study in the strict sense, it provides a clear view of how our fully automated training pipeline performs relative to conventional supervised training. Overall, we observe that models trained with *VisPlay* achieve competitive average accuracy compared with those trained on real, human-written data. While performance on several task categories differs slightly, the general trend indicates that the self-evolving process can produce training signals of sufficient quality to improve base VLMs capabilities. These findings suggest that even in settings where human annotations are costly, limited, or unavailable, our framework can still serve as an effective and scalable alternative, enabling VLMs to develop stronger generalization abilities without depending on manual supervision.

## 3.4. Co-Evolution Dynamics of Two Roles

- **The Evolution of Question Difficulty and Solution Accuracy.** To analyze the co-evolution dynamics of the two roles, we examine the changes in question difficulty (orange, left axis) and problem-solving accuracy (blue, right axis) across three VLMs during the first training iteration (Figure 3). Question difficulty is operationalized as the Reasoner's model-perceived difficulty, derived from the

Table 3. Performance comparison between *VisPlay* and standard GRPO training with human-labeled data. Although *VisPlay* relies entirely on self-generated supervision, it achieves competitive overall accuracy and significantly reduces hallucination. This demonstrates that our self-evolving framework can meaningfully enhance VLM performance even in the absence of human-annotated datasets.

| Methods | General Visual Understanding | | | | Visual Math | | Hallucination | Avg. |
|---|---|---|---|---|---|---|---|---|
| | MMMU | MM -Vet | RealWorld QA | VisNum Bench | Math Verse | MATH -Vision | Hallusion Bench | |
| *Qwen2.5-VL-3B-Instruct* | | | | | | | | |
|    Standard GRPO | 40.3 | 49.5 | 63.0 | 36.7 | 42.8 | 29.9 | 67.4 | 47.1 |
|    *VisPlay* (Iter 3) | 37.1 | 38.1 | 71.9 | 39.2 | 35.2 | 30.0 | 90.5 | 47.3 |
| *Qwen2.5-VL-7B-Instruct* | | | | | | | | |
|    Standard GRPO | 39.8 | 51.8 | 66.6 | 43 | 53.2 | 33.8 | 66.6 | 50.7 |
|    *VisPlay* (Iter 3) | 38.3 | 46.3 | 69.7 | 32.6 | 39.1 | 31.2 | 92.3 | 48.6 |

Table 4. Examples of challenging questions generated by the self-evolving Vision-Language model across three training iterations. The questions progressively increase in complexity, illustrating the growth in difficulty of the Questioner's outputs over iterations. Images on the left and right correspond to the visual context for each question. The questions are raised by Qwen2.5-VL-3B-Instruct.

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**Challenging Examples from Self-Evolving Trained Vision-Language Model**



| | | |
|---|---|---|
| Question (Iter 1) | Approximately how many lung fields are visible in the X-ray image? | Which skeletal structure most likely belongs to a bird with hollow bones? |
| Question (Iter 2) | On a thoracic x-ray, the right lobe of the lung is more spread out compared to the left lobe. If the right lobe is given a score of 1 and the left lobe is given a score of 0, what is the difference in scores between the right and left lung lobes? | On which figure does the long neck of the dinosaur have the greatest horizontal angle with the vertical axis? |
| Question (Iter 3) | On which rib is the line approximately 2.5 cm above the image's midpoint? | Which skeletal structure is most likely to have evolved secondary to flying abilities and which is less likely to have this trait? |

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confidence score defined in Eq. 4 in Section 2.3. Across all models, a consistent co-evolution pattern emerges. The Image-Conditioned Questioner's difficulty curves exhibit a general upward trend, with initial increments followed by sustained growth, indicating the role's ability to progressively formulate more challenging visual questions. Concurrently, the Multimodal Reasoner's accu-

racy curves, despite minor fluctuations, show a complementary upward trajectory. This means that as question difficulty rises, the Reasoner adapts and enhances its problem-solving capability, with both metrics reinforcing each other's improvement over iterations. Such mutual reinforcement validates *VisPlay*'s core mechanism, where the two interacting roles drive scalable self-evolution in

multimodal reasoning.

- **The Evolution of Capabilities and Data Accuracy.** Building on the interaction between question difficulty and solution accuracy, we further analyze how the Reasoner's capabilities and the quality of pseudo-labeled data evolve across iterations. For each training iteration, the Questioner generates questions for the same 200 images, and Reasoners from each iteration attempt to answer them. As shown in Table 2, the Reasoner's accuracy steadily improves across iterations (e.g., from 44.0 to 49.0 on first-iteration questions), while the estimated accuracy of pseudo-labels slightly declines (from 72 to 61), reflecting increasing question difficulty. These trends highlight the co-evolution of model reasoning ability and data complexity during self-improving training.

## 3.5. Case Study on Question Difficulty Evolution

Table 4 presents example questions generated by the self-evolving Vision-Language Models across three training iterations. Iteration 1 questions focus on direct observation, such as counting or identifying objects. Iteration 2 introduces relational and comparative reasoning, requiring the model to assess differences or evaluate spatial angles. Iteration 3 further increases complexity with multi-step reasoning and inference, including precise localization and causal relationships. This progression demonstrates a systematic increase in question difficulty, providing increasingly challenging training signals that encourage the model to adapt and improve its reasoning capabilities. Such a design ensures that both the Questioner and Reasoner co-evolve, progressively enhancing the overall performance of the system.

## 4. Related Work

**Post-Training for Vision-Language Models**  Recent research in post-training of vision-language models (VLMs) has shifted from supervised fine-tuning (SFT) toward reinforcement learning (RL) paradigms, driven by the increasingly strong capabilities of pre-trained VLMs. Earlier works such as LLaVA [17, 27] primarily rely on SFT to align a language model backbone with a visual information via a projection layer, enabling multimodal instruction-following and visual reasoning. However, as base model quality improves, RL-based post-training has emerged as a more powerful alternative. In particular, R1-style training [10, 18, 53] has gained attention for its ability to enhance reasoning and visual understanding without explicit supervision. A key insight behind this success is that RL becomes effective only when the base model is sufficiently capable to self-explore reasoning trajectories [1, 7, 21, 22]. Despite these advances, most existing RL-based VLM approaches still depend on annotated multimodal datasets, which are costly and difficult to scale [11, 12, 24, 31, 42, 49]. To reduce reliance on human supervision, several re-

cent works explore VLM self-play paradigms in games. Vision-Zero [38] and Game-RL [36] train VLMs with simulated game data to improve their general reasoning ability. Nonetheless, these methods often continue to depend on external models or tools for training data generation. While large language models (LLMs) have demonstrated self-evolving learning dynamics without any human or model-labeled data, extending such paradigms to VLMs remains more challenging due to the additional visual modality.

**Self-Evolving In Large Language Models**  Recent work has focused on enabling large language models (LLMs) to self-evolve their reasoning capabilities with minimal to zero human supervision. Various approaches have been proposed to achieve this. General unsupervised self-training frameworks like Genius [44] and Deep Self-Evolving Reasoning [29] aim for advanced reasoning. A common theme is data-free training or starting from zero data, as explored in R-Zero [16], Absolute zero [51], and Language self-play [19]. Other methods adapt self-play for specific goals or environments. For example, SPICE [26] improves reasoning in corpus environments, Search Self-play [30] pushes capabilities via search, and SPELL [46] focuses on evolving long-context models. Additionally, some methods utilize interactions between multiple agents to collectively bootstrap reasoning abilities, as seen in Socratic-Zero [39] and Multi-Agent Evolve [4].

## 5. Limitation

While our work introduces a scalable, self-evolving framework, we acknowledge two primary limitations that suggest directions for future research. First, due to computational constraints, our experiments were limited to the Qwen2.5-VL and MiMo-VL families. The scalability and effectiveness of *VisPlay* on significantly larger VLMs (e.g., $\geq$ 10B parameters) is still an important open question. Second, our framework lacks a definitive verification method for the self-generated data. While our GRPO policy indirectly optimizes for quality, developing more robust, automated methods to verify data faithfulness and prevent error accumulation is a key area for future investigation.

## 6. Conclusion

We present *VisPlay*, a self-evolving RL framework that enables vision-language models to autonomously improve from unlabeled images. By decomposing a VLM into an Image-Conditioned Questioner and a Multimodal Reasoner and optimizing them via GRPO, our method balances challenge and accuracy without human supervision. Experiments show consistent gains in reasoning, compositional generalization, and hallucination reduction across multiple benchmarks. *VisPlay* demonstrates that scalable,

self-improving multimodal intelligence is achievable. By iteratively generating and learning from its own experiences, a model can refine its capabilities beyond human-labeled data. This framework opens avenues for richer multimodal interactions and cross-domain adaptation, pointing toward intelligence systems that can continually evolve autonomously. Our results suggest a promising path toward truly autonomous vision-language systems that improve themselves over time.

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# *VisPlay*: Self-Evolving Vision-Language Models from Images

## Supplementary Material

## A.1 Detailed Training Dataset and Benchmarks

**Training Dataset**   We use the image data from Vision-47K dataset [12, 25], which contains 47,000 web-sourced images covering a wide variety of domains. The dataset includes charts, medical images, educational exams, textbook illustrations, and driving simulation frames. For our purposes, we exclusively use the images themselves, omitting any associated questions and answers. The dataset consists of approximately 10K charts, 8K medical images, 12K educational images (from exams and textbooks), 7K driving scenes, and 10K miscellaneous images from various domains. All images were standardized to a resolution of $224 \times 224$ pixels for model training.

**Backbone Models and Training**   We trained three backbone models using *VisPlay*:
- **Qwen2.5-VL-3B-Instruct**[4]: 3 billion parameters, fine-tuned with multimodal instruction data to enhance reasoning over visual-text tasks.
- **Qwen2.5-VL-7B-Instruct**[5]: 7 billion parameters, trained under the same protocol with extended batch sizes and longer training schedules to improve complex reasoning and generalization.
- **Mimo-VL-7B-SFT**[6]: 7 billion parameters, optimized with supervised fine-tuning on multimodal datasets for better alignment with human instructions.

**General Visual Understanding**   Four established benchmarks are used:
- **MM-Vet** [47]: Evaluates recognition, OCR, and visual math abilities using a unified LLM-based scoring metric. The dataset contains over 5,000 test samples with detailed scoring for each subtask.
- **MMMU** [48]: Cross-modal reasoning benchmark with 11.5K college-level multiple-choice questions spanning six academic disciplines. Each question is image-based and designed to test subject knowledge and reasoning ability.
- **RealWorldQA** [41]: Contains approximately 700 real-world images paired with spatially grounded questions.

Evaluation emphasizes spatial reasoning and contextual understanding.
- **VisNumBench** [40]: Focused on visual number sense, includes roughly 1.9K questions involving numerical attributes, comparisons, and estimations.

**Multimodal Mathematical Reasoning**   Two specialized benchmarks:
- **MathVerse** [50]: 2.6K diagram-centric questions covering geometry, functions, and algebra, provided in multiple visual-text formats.
- **MATH-Vision** [37]: Approximately 3K competition-level problems across 16 subjects and five difficulty tiers. Focuses on integrating visual information into advanced mathematical reasoning.

**Visual Hallucination Detection**   HallusionBench [14] is used to identify model errors caused by either language-only hallucinations or visual illusions. Evaluation is conducted in a simple yes/no format, enabling precise measurement of hallucination rates and error types.

## A.2 Training Configuration

**Image-based Questioner Configuration.** The Questioner is trained using a vision–language model with a maximum context window of 8192 tokens. The training set consists of 47K multimodal samples (Vision-SR1-47K), and evaluation is performed on the MMStar benchmark. Each sample uses `problem`, `answer`, and `images` as the prompt, label, and image fields, respectively. During rollouts, the Questioner generates 8 candidate questions per input. Training runs for 10 epochs with 20 gradient-update steps, using 4 GPUs in data-parallel mode. The model parameters are loaded from a specified Questioner checkpoint, and all checkpoints are saved under the designated experiment directory. Validation before training is disabled to maximize efficiency during early-stage learning.

**Multimodal Reasoner Configuration.** The Solver is trained using chain-of-thought reinforcement learning. Its output length is capped at 4096 tokens, and prompts are constructed using a dedicated Jinja template to enforce a consistent reasoning format. Training uses the self-play dataset produced by the Questioner, while evaluation again

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You are an intelligent Question Generator. Your task is to create a question based on the given image.
Requirements (must follow exactly):
1. Analyze the image carefully and understand all details. 2. Generate exactly one question that is directly related to the image. 3. Choose the question type from only one of the following: - multiple choice (Yes/No or four options labeled A, B, C, D; only one correct answer) - numerical (requires a specific numeric answer) - regression (requires predicting a continuous value, such as a measurement, quantity, or coordinate) 4. The question must require analysis or reasoning, not just description. 5. Provide the correct answer. Include units if applicable. 6. Output must be strictly in this format, with nothing else: 7. Question type must be only one of: multiple choice, numerical, regression.

The following THREE blocks:
$< type > X < /type >$
$< question > Y < /question >$
$< answer > Z < /answer >$
Strict rules: - Do not use any other labels, punctuation, or formatting. - Do not add commentary, explanations, or extra text. - X must be exactly one of: multiple choice, numerical, or regression. - Always use the exact three-line structure above. - Do NOT include any units; provide only the numeric value or option. Example of correct output:
$< type > numerical < /type >$
$< question > How \ many \ clubs \ are \ there < /question >$
$< answer > 5.7M < /answer >$

**Multimodal Reasoner Prompt Template**

Please reason step by step carefully based on the question: + content + and the image. After completing your reasoning, you MUST output the final, clean, and concise answer strictly inside + \boxed{} + . The final answer MUST appear inside \boxed{}, and nowhere else. If there is no boxed answer, your response is considered incorrect.

**LLM-as-Judge Prompt Template**

You are an answer evaluation assistant. Your task is to judge whether two answers are substantially equivalent. When evaluating, you should ignore superficial differences such as format, spaces, punctuation, case, etc., and focus on whether they are consistent in core content, logical meaning and information expression. The judgment criteria should be lenient and inclusive, as long as the expressed meaning is basically the same, it is considered equivalent.

uses MMStar. To ensure stable learning under long sequences, we adopt a conservative micro-batch size of 1 for both updates and experience rollouts. The rollout engine supports up to 20K batched tokens per forward pass. Reward computation is performed by a custom scoring function that evaluates the correctness of the solver's predicted final answer; the same function is applied for validation-time reward estimation. Training is conducted for 10 epochs with 20 total optimization steps, and checkpoints are stored under the experiment directory specified by the user.

## A.3 Prompt Templates

The following three prompt templates define the core interaction structure used in our self-evolving Vision-Language Model. In this setup, multiple specialized roles—such as a question generator, a multimodal reasoner, and an evaluator—are orchestrated to form an autonomous learning loop. Each template specifies precise behavioral constraints that allow the model to generate tasks, solve them with step-by-step reasoning, and assess answer consistency. Together, these components establish a controlled self-play environment that enables the model to iteratively refine its reasoning capabilities without relying on external supervision.