DEFACTO: COUNTERFACTUAL THINKING WITH IMAGES FOR ENFORCING EVIDENCE-GROUNDED AND FAITHFUL REASONING

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ABSTRACT

Recent advances in multimodal language models (MLLMs) have achieved remarkable progress in vision-language reasoning, especially with the emergence of "thinking with images," which integrates explicit visual steps into the reasoning process. While this paradigm strengthens image-based reasoning, a significant challenge remains: models may arrive at correct answers by relying on irrelevant or spurious regions, driven by prior knowledge or dataset biases. Even when the answer is correct, flawed reasoning indicates that the model has not truly understood the image, highlighting the critical importance of reasoning fidelity in multimodal tasks. To address this issue, we propose *DeFacto*, a counterfactual reasoning framework that jointly enforces accurate answering and faithful reasoning. A key component of our approach is the design of three complementary training paradigms: (i) positive, (ii) counterfactual, and (iii) random-masking. To enable these paradigms, we develop a pipeline that automatically localizes question-relevant evidence and constructs positive, counterfactual, and random variants, resulting in a dataset of about 100k images. Building on this framework, we train multimodal language models with GRPO-based reinforcement learning, where we design three complementary rewards to guide the model toward accurate answering and evidence-grounded reasoning. Experiments on diverse benchmarks demonstrate that *DeFacto* substantially improves both answer accuracy and reasoning faithfulness, establishing a stronger foundation for interpretable multimodal reasoning. The code and datasets will be released upon acceptance.

1 INTRODUCTION

Vision-language models (VLMs) Alayrac et al. (2022); Li et al. (2023); Zhu et al. (2023); Liu et al. (2023; 2024a); Peng et al. (2023); Bai et al. (2023); Team et al. (2023); Chen et al. (2024c;b) have achieved remarkable progress in recent years, demonstrating strong capabilities across a wide range of multimodal tasks such as visual question answering, image captioning, and referring expression comprehension. By leveraging large-scale pretraining and cross-modal alignment, these models can generate fluent and semantically relevant outputs grounded in visual context. However, in complex scenarios that require multi-step reasoning or fine-grained perception, existing models often rely heavily on implicit language priors, producing plausible yet unfaithful responses that are weakly grounded in the actual image. Instead of genuinely learning to reason over visual content, these models often fall back on text-based chain-of-thought patterns, limiting their ability to handle cases where critical evidence must be directly perceived from the image.

Recent advances in "thinking with images" Microsoft (2024); OpenAI (2025) emphasize the integration of explicit visual steps into the reasoning process to enhance transparency and visual grounding. Early approaches employ supervised fine-tuning (SFT) Ouyang et al. (2022); Touvron et al. (2023); Liu et al. (2023); Dettmers et al. (2023), where models are trained in a chain-of-thought (CoT) Shao et al. (2024) manner to produce region-aware reasoning traces based on manually annotated visual steps. To reduce the annotation burden, subsequent works explore reinforcement learning strategies that allow models to autonomously develop visual interaction behaviors such as region cropping, attention shifting, or zooming Zheng et al. (2025); Cao et al. (2025); Liu et al. (2025b); Zhang et al. (2025b). Yet these approaches do not guarantee that the reasoning chains are faithful to the actual vi-

Figure 1: Qualitative examples of failure cases. Left: Mislocalized Failure (park scene). Right: Spurious Correctness (road scene).

sual evidence: since the model still has access to the entire image, it may either produce an incorrect answer by focusing on irrelevant regions or arrive at the correct answer even when the highlighted regions are unrelated. This issue is clearly illustrated in Fig. 1, where most existing models exhibit two characteristic error modes: *Mislocalized Failure*, in which the model selects irrelevant regions and consequently produces an incorrect answer, and *Spurious Correctness*, in which the answer happens to be correct even though the selected regions are unrelated to the reasoning process. In the park scene (left), GRIT mistakenly attends to the distant background, while Deepeyes zooms in on a faint and indistinct fallen leaf, both of which fail to capture the evidence and lead to an incorrect answer. In the road scene (right), GRIT fixates on the ground, and Deepeyes again zooms in on a helmeted rider, producing a reasoning path that contradicts the very premise of the question. These cases reveal a deeper problem: current approaches can still succeed superficially even when their reasoning is disconnected from the actual evidence. However, correct answers alone are not sufficient—the reasoning process itself must also be correct, since flawed reasoning often leads to erroneous predictions. Such superficial success leads to poor generalization on out-of-distribution inputs and undermines trustworthiness in downstream applications that demand evidence-based decisions. What is needed is a training paradigm that enforces both correct evidence selection and correct answering, ensuring that reasoning trajectories and final predictions are jointly faithful to the visual input.

Motivated by these failure cases, we introduce *DeFacto*, a counterfactual reasoning framework that aligns reasoning trajectories with visual evidence, ensuring predictions are both reliable and interpretable. The core idea is to employ three complementary training forms that jointly constrain the model's behavior: (i) positive supervision, (ii) counterfactual abstention, and (iii) random masking to strengthen evidence-grounded reasoning. In the positive case, the model is given the original image and trained to predict bounding boxes that cover the essential evidence together with the correct answer, receiving positive feedback only when both the evidence selection and the answer are correct. In the counterfactual case, the same question is paired with an image where the evidence regions $\mathcal{R}^+$ have been masked; since the necessary visual evidence is no longer available, the model is expected to abstain by outputting a designated token such as "unknown," while any concrete an-

swer is penalized. In the random-masking case, irrelevant regions $\mathcal{R}^-$ are masked independently of the question, preventing the model from exploiting superficial correlations between the presence of masks and abstention behavior. Training is performed with GRPO-based reinforcement learning, where the reward integrates three components: (i) Answer Correctness Reward, (ii) Format Consistency Reward, and (iii) Region Selection Coherence Reward. Through this design, DeFacto compels the model to produce reasoning that is logically grounded, answers that are accurate, and predictions where reasoning and outcomes remain consistent.

In practice, constructing counterfactual samples requires reliably identifying the question-relevant regions. To this end, we adopt a structured two-stage extraction pipeline. First, a multimodal language model (Qwen2.5-VL Bai et al. (2025)) parses the question and generates a set of key descriptors (e.g., "the red cup," "the text on the shirt"). Next, candidate regions in the image are obtained from a region proposal network (RPN) Ren et al. (2015) and an OCR module Islam et al. (2017). The OCR regions are further matched with textual descriptors to capture evidence critical for text-centric questions. For visual objects, the descriptors are fed into an open-vocabulary detector (DINO-X Ren et al. (2024)), which provides bounding boxes that serve as positive evidence regions. Finally, the remaining proposals from the RPN, after removing matched positives, are treated as irrelevant regions for counterfactual construction. Using this pipeline, we construct a counterfactual dataset about 100k images, ensuring that positive, counterfactual, and random-masking instances differ only in the availability of essential evidence while preserving unrelated context. Building on this dataset, the model is further optimized with GRPO-based reinforcement learning. This training paradigm enforces consistency between evidence selection and final predictions, ensuring that reasoning traces remain faithful to visual cues. As illustrated in Fig. 1, our method consistently grounds its reasoning in the correct regions (e.g., focusing on the three motorcycles on the road and their passengers), thereby unifying reasoning steps with faithful visual evidence.

Our main contributions are threefold:

(1) We propose a counterfactual "thinking with images" framework that aligns the reasoning process with essential visual evidence by jointly optimizing for answer correctness and region-level faithfulness via reinforcement learning. (2) We construct a new counterfactual dataset about 100k images using a language-guided algorithm that integrates open-vocabulary detection with targeted masking, ensuring that only question-relevant regions are removed while irrelevant context is preserved. (3) We demonstrate, through extensive experiments on diverse benchmarks, that our approach consistently improves both answer accuracy and visual grounding faithfulness over strong baselines.

2 Related Work

Structured Thinking with Images in Vision-Language Models. The concept of "thinking with images" was initially highlighted in OpenAI o3 Achiam et al. (2023); OpenAI (2025) and later explored in works like COGCOM Qi et al. (2024) and GRIT Fan et al. (2025). Existing approaches can be broadly categorized into two classes: those that inject visual information into the reasoning process as explicit intermediate steps, and those that enhance region selection and visual grounding through learning or optimization. The first category includes GRIT, which combines natural language and bounding boxes via reinforcement learning; REFOCUS Fu et al. (2025), which formulates visual editing as intermediate reasoning steps; COGCOM Qi et al. (2024), which models reasoning as visual manipulations such as cropping and OCR; and VisionReasoner Liu et al. (2025a), which unifies detection, segmentation, and counting under one framework. The second category emphasizes grounding quality. Fast-and-Slow Visual Agents Sun et al. (2024) model dual-system reasoning. DeepEyes Zheng et al. (2025) leverages reinforcement learning to train multimodal chains-of-thought and dynamically invoke zoom-in tools when visual evidence is ambiguous. MLLMs Know Where to Look Zhang et al. (2025a) improves small-object perception by applying inference-time cropping strategies to highlight fine details. Chain-of-Focus Zhang et al. (2025b) further adapts zoom-in operations through reinforcement learning, enabling multi-scale reasoning across cluttered scenes. Ground-R1 Cao et al. (2025) enhances faithfulness by introducing explicit reward signals that align reasoning outputs with grounded evidence. V* Wu & Xie (2024) formulates guided visual search as a core cognitive mechanism to explore high-resolution images efficiently. Visual-RFT Liu et al. (2025b) refines grounding via reinforcement fine-tuning. As a result, they often fail to ensure

that reasoning trajectories remain consistent with the visual evidence, leaving open the need for a paradigm that jointly enforces faithful reasoning steps and accurate answers.

Counterfactual Reasoning in Vision-Language Models. Counterfactual reasoning in VLMs can be categorized into two types: counterfactual data generation and inference-based reasoning. The first enhances robustness by constructing or augmenting counterfactual samples to reduce bias and hallucination. For example, Learning Chain of Counterfactual Thought Zhang et al. (2020) disentangles factual knowledge from reasoning via CoBRa and CoCT datasets; C-VQA Zhang et al. (2024b) and CRIPP-VQA Patel et al. (2022) construct benchmarks for counterfactual VQA in static and video settings, respectively; Counterfactual Vision and Language Learning Abbasnejad et al. (2020) and Counterfactual Contrastive Learning Zhang et al. (2024c) generate counterfactuals through structural causal models and perturbation strategies, while CounterCurate Zhang et al. (2024a) improves compositional reasoning by augmenting training data with physically grounded examples and semantic counterfactuals using generative models. The second type focuses on inference with mechanisms such as Counterfactual-based Saliency Maps Wang et al. (2023) for contrastive visual explanation, DiG-IN Augustin et al. (2024) for diffusion-guided latent edits, and Counterfactual VQA Niu et al. (2021) for causal effect modeling. However, most existing approaches either treat counterfactuals as data augmentation without explicitly constraining the reasoning process, or apply them only at inference for explanation, leaving a gap in methods that can jointly enforce faithful reasoning steps and correct answers during training.

3 METHOD

In this section, we present the overall framework of DEFACTO, our counterfactual "thinking with images" approach. This section is organized into three parts: (1) the overall architecture and inference pipeline (Section 3.1); (2) the construction of counterfactual datasets via region masking and open-vocabulary filtering (Section 3.2); and (3) the reinforcement learning strategy with a tailored reward design that guides the model toward accurate answering, faithful reasoning, and their consistency (Section 3.3).

3.1 OVERALL FRAMEWORK

DEFACTO is a vision-language reasoning framework that enforces region-level faithfulness in multimodal question answering. It is designed to teach models not only *where to look* in the image but also *when to abstain* if the necessary evidence is absent. By combining structured prompting with counterfactual supervision, DEFACTO aligns the reasoning process with visual evidence rather than spurious correlations.

As illustrated in Figure 2, given a question and an image, the model is prompted to produce outputs in a structured format consisting of three fields. The `<bbox>` field contains one or more bounding boxes encoded as JSON objects of the form $\{\text{Position} : [x_1, y_1, x_2, y_2], \text{Confidence} : p\}$, the `<think>` field records a short rationale, and the `<answer>` field provides the final prediction. Multiple boxes can be returned when multiple evidence regions are required. If no valid evidence exists, the model outputs `unknown` in both the `<bbox>` and `<answer>` fields. This structured format ensures that every reasoning trajectory is explicitly tied to visual evidence through bounding boxes and aligned with the model's final answer. Training is based on three complementary supervision forms. In the positive case, evidence-bearing regions remain visible and the model is rewarded for selecting them and producing the correct answer. In the counterfactual case, these regions are masked, and the model is expected to abstain by outputting `unknown`. In the random-masking case, irrelevant regions are occluded to prevent shortcut learning from superficial mask patterns. Together, these three forms establish a consistent learning signal that requires both the reasoning path and the answer to be faithful to the underlying visual support.

3.2 COUNTERFACTUAL DATASET CONSTRUCTION

Positive, Counterfactual, and Random Instances. Let $\mathcal{R} = \{r_1, r_2, \ldots, r_n\}$ denote the set of candidate regions in an image I, obtained from a region proposal network (RPN) Ren et al. (2015) together with OCR to cover both object-level and text-bearing regions. Among them, $\mathcal{R}^+ \subseteq \mathcal{R}$ represents the evidence regions that are critical to answering the question q, while $\mathcal{R}^- = \mathcal{R} \setminus \mathcal{R}^+$

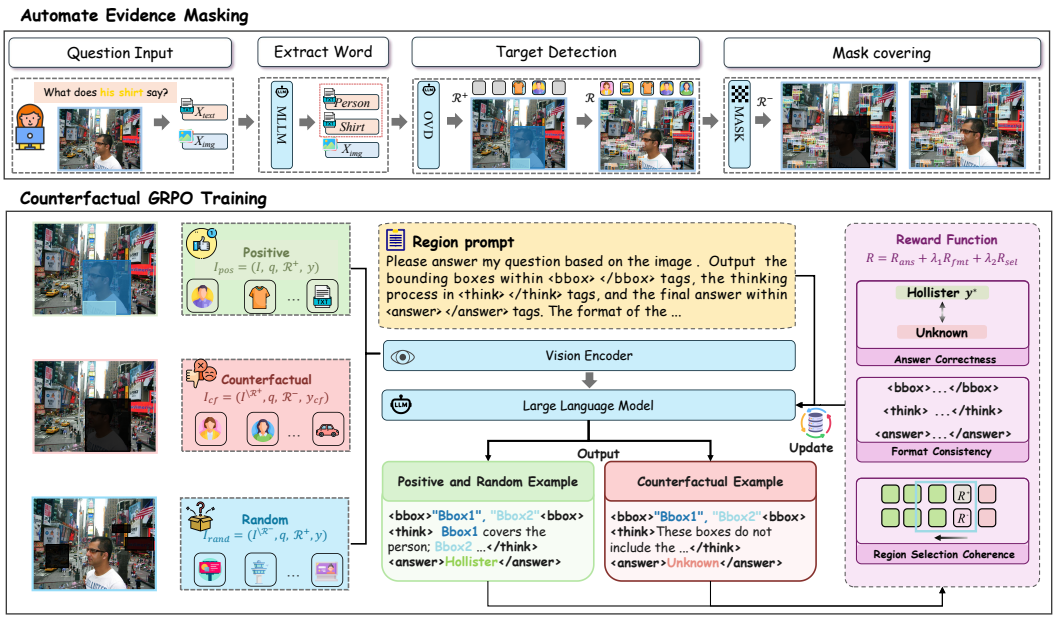

Figure 2: An overview of our counterfactual framework with three inputs: positive (full evidence), counterfactual (masked evidence), and random (masked irrelevant regions), guiding the model to answer correctly or abstain with "unknown."

denotes the remaining irrelevant regions. Based on these definitions, we construct three complementary training instances:

$$I_{\text{pos}} = (I, q, \mathcal{R}^+, y) \qquad I_{\text{cf}} = (I^{\setminus \mathcal{R}^+}, q, \mathcal{R}^-, y_{\text{cf}}) \qquad I_{\text{rand}} = (I^{\setminus \mathcal{R}^-}, q, \mathcal{R}^+, y), \tag{1}$$

where y is the ground-truth answer, I_{pos} is the positive instance with evidence regions available, I_{cf} is the counterfactual instance where evidence regions are masked and the abstention label y_{cf} (e.g., "Unknown") is required, and I_{rand} is the random-masking instance where irrelevant regions are occluded to prevent shortcut learning.

Construction Process. To automatically construct I_{pos}, I_{cf}, and I_{rand} without manual annotations, we follow three steps:

(1) Descriptor extraction. Given an image I and a question q, we employ a MLLM (Qwen2.5-VL Bai et al. (2025)) to extract a set of key descriptors:

$$\text{MLLM}(I, q) = \{d_1, d_2, \ldots, d_m\}, \tag{2}$$

where each d_i is a textual phrase (e.g., an object, attribute, or relation) that captures the visual concepts in I explicitly mentioned or implied by q. As illustrated in Fig. 2 ("Automate Evidence Masking"), for the question "What does his shirt say?", the MLLM decomposes the query into descriptors such as "a man" and "man's shirt" as the critical evidence.

(2) Evidence localization. Let $\mathcal{R} = \{r_1, \ldots, r_n\}$ be the set of candidate image regions. We employ the open-vocabulary detector DINO-X Ren et al. (2024), which computes grounding scores $\text{OVD}(r, k)$ for each $r \in \mathcal{R}$ and $k \in \mathcal{K}(q)$. Based on these scores, the regions are partitioned into evidence and irrelevant sets:

$$\mathcal{R}^+ = \{r \in \mathcal{R} \mid \max_{k \in \mathcal{K}(q)} \text{OVD}(r, k) > \tau\}, \qquad \mathcal{R}^- = \mathcal{R} \setminus \mathcal{R}^+, \tag{3}$$

where τ is a confidence threshold. In the street example, $\mathcal{R}^+$ corresponds to bounding boxes covering the signboard, while $\mathcal{R}^-$ contains all other regions.

(3) Instance generation. Once $\mathcal{R}^+$ and $\mathcal{R}^-$ are obtained, the positive, counterfactual, and random-masking instances are directly constructed as defined in Eq. 1.

For counterfactual dataset construction, we leverage a broad collection of visual question answering and document understanding benchmarks, including VQAv2 Goyal et al. (2017), OKVQA Marino et al. (2019), GQA Hudson & Manning (2019), ScienceQA Lu et al. (2022), VizWiz Gurari et al. (2018), TextVQA Singh et al. (2019), OCRVQA Mishra et al. (2019), AI2D Kembhavi et al. (2016), DocVQA Mathew et al. (2021), ChartQA Masry et al. (2022), InfoVQA Mathew et al. (2022), DeepForm Svetlichnaya (2020), Kleister KLC Stanisławek et al. (2021), WikiTableQuestions (WTQ) Pasupat & Liang (2015), TabFact Chen et al. (2019), and VisualMRC Tanaka et al. (2021). This diverse coverage ensures that counterfactual supervision is tested across natural images, scientific diagrams, documents, charts, tables, and multi-source reasoning tasks. Representative visualizations of the constructed dataset are provided in Appendix H (Figures 4–19).

3.3 Reinforcement Learning Training

Sequential Reasoning Formulation. We formulate the reasoning process of DeFacto as a Markov Decision Process (MDP), where the model interacts with the question and image in a sequential manner. At each step, the state s_t encodes the multimodal context, including the input question, the image representation, and the history of previously predicted regions. The policy π_θ then outputs either a new bounding box that localizes question-relevant evidence or a special `STOP` token to terminate the process.

Formally, the state at step t is defined as

$$s_t = \{q, f_v(I), B_{<t}\}, \tag{4}$$

where q is the question, $f_v(I)$ the image representation, and $B_{<t}$ the set of bounding boxes predicted before step t. The rollout continues until `STOP` is emitted or the maximum step limit is reached, and the final answer is generated based on the accumulated trajectory.

Reward Design. To make training effective, we design three reward components. (1) *Answer Correctness Reward*: encourages correct answers in positive/random cases, rewards "Unknown" in counterfactual cases, and penalizes unsupported guesses. (2) *Format Consistency Reward*: ensures outputs strictly follow the required schema. (3) *Region Selection Coherence Reward*: promotes overlap with evidence regions $\mathcal{R}^+$ and penalizes overlap with irrelevant regions $\mathcal{R}^-$, with no reward in counterfactual cases.

The overall training signal combines these components into the composite reward in Eq. 5.

$$R \;=\; R_{\text{ans}} \;+\; \lambda_1 \, R_{\text{fmt}} \;+\; \lambda_2 \, R_{\text{sel}}, \tag{5}$$

1. Answer Correctness Reward. To enforce correct behavior across the three training forms, we define

$$R_{\text{ans}} = \begin{cases} \mathsf{acc}(\hat{y}, y^*) \;-\; \underbrace{\gamma_{\text{unk}}\, \mathsf{unk}(\hat{y})}_{\text{penalize "Unknown"}}, & t \in \{\text{pos}, \text{rand}\}, \\[2ex] \underbrace{\rho_{\text{unk}}\, \mathsf{unk}(\hat{y})}_{\text{reward "Unknown"}} \;-\; \underbrace{\gamma_{\text{guess}}\, [1 - \mathsf{unk}(\hat{y})]}_{\text{penalize guess}} \;-\; \underbrace{\gamma_{\text{corr}}\, \mathbf{1}[\hat{y} = y^*]}_{\text{penalize even if correct}}, & t = \text{cf}, \end{cases} \tag{6}$$

where $\mathsf{acc}(\hat{y}, y^*) \in \{0, 1\}$ indicates answer correctness, and $\mathsf{unk}(\hat{y}) \in \{0, 1\}$ indicates an "Unknown" response. Here $\gamma_{\text{unk}} > 0$ penalizes answering "Unknown" in positive or random cases, $\rho_{\text{unk}} > 0$ rewards "Unknown" in counterfactual cases, $\gamma_{\text{guess}} > 0$ penalizes any concrete guess in counterfactual cases, and $\gamma_{\text{corr}} > \gamma_{\text{guess}}$ applies an even stronger penalty when the model outputs the correct answer y^* without access to evidence.

2. Format Consistency Reward. We encourage well-formed outputs and valid region indices selected from the prompt:

$$R_{\text{fmt}} \;=\; \begin{cases} \alpha, & \text{if output follows the required schema and indices are valid,} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

Here, the "required schema" refers to the presence of `<think>...</think>` for the reasoning process, `<bbox>...</bbox>` for the predicted bounding boxes, and `<answer>...</answer>` for the final answer. In particular, the `<bbox>` field must contain well-formed bounding box coordinates in the format `[x1, y1, x2, y2]`, ensuring that the model explicitly grounds its predictions on localized visual regions.

3. Region Selection Coherence Reward. Let $B = \{\text{bbox}^1, \ldots, \text{bbox}^k\}$ be the set of bounding boxes predicted before `STOP`. We define the overlap scores with evidence regions $\mathcal{R}^+$ and irrelevant regions $\mathcal{R}^-$ as

$$\phi^+(b) = \max_{r \in \mathcal{R}^+} \text{IoU}(b, r), \quad \phi^-(b) = \max_{r \in \mathcal{R}^-} \text{IoU}(b, r).$$

The reward is then defined as

$$R_{\text{sel}} = \begin{cases} \beta_{\text{pos}} \frac{1}{|B|} \sum_{b \in B} \phi^+(b) \; - \; \beta_{\text{neg}} \frac{1}{|B|} \sum_{b \in B} \phi^-(b), & t \in \{\text{pos}, \text{rand}\},\ B \neq \varnothing, \\ -\gamma_{\varnothing}, & t \in \{\text{pos}, \text{rand}\},\ B = \varnothing, \\ 0, & t = \text{cf}. \end{cases} \tag{8}$$

with $\beta_{\text{pos}}, \beta_{\text{neg}}, \gamma_{\varnothing} > 0$.

The full training dynamics of each reward component, along with the corresponding hyperparameter settings, are provided in the Appendix (see Fig. 3 and Table 5).

Training Strategy. Unlike prior works that require a supervised warm-up stage, we directly fine-tune Qwen2.5-VL with reinforcement learning, using Group Relative Policy Optimization (GRPO) and the composite reward in Eq. 6 and Eq. 8. GRPO compares multiple rollouts within a group and rewards each according to its improvement over the group average, eliminating the need for a value network and reducing variance. The objective is defined as:

$$\mathcal{L}_{\pi}(\theta) \; = \; \mathbb{E}_i \left[\frac{\pi_\theta(\tau^{(i)})}{\pi_{\theta_{\text{old}}}(\tau^{(i)})} \left(R(\tau^{(i)}) - \frac{1}{M} \sum_{j=1}^{M} R(\tau^{(j)}) \right) \right], \tag{9}$$

where we set the group size $M = 4$ to balance stability and exploration during training. Figure 3 shows the learning dynamics of the three reward components defined in Eq. 6 and Eq. 8, as well as the total reward.

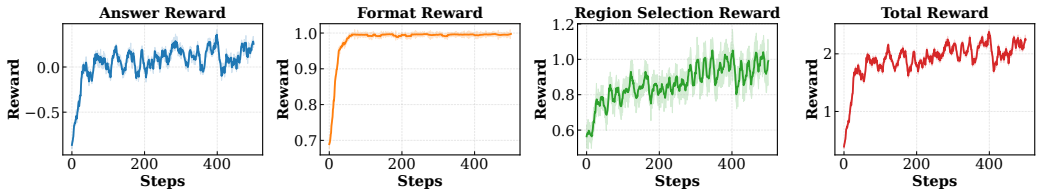

Figure 3: Reward curves during training. Each subplot corresponds to one component of the reward: (a) Answer Reward, (b) Format Reward, (c) Region Selection Reward, and (d) Total Reward. Solid lines denote the mean across runs, and shaded areas denote standard deviation.

4 Experiment

4.1 Setup

Baselines. We compare DeFacto against a broad set of recent approaches that explicitly incorporate visual reasoning into multimodal language models. Specifically, we include Qwen2.5-VL Bai et al. (2025), a strong pretrained backbone widely used for visual understanding; ViCrop Zhang et al. (2025a), which improves small-object perception via inference-time cropping; GRIT Fan et al. (2025), which integrates grounded reasoning traces through reinforcement learning; DeepEyes Zheng et al. (2025), which incentivizes models to call visual tools during reasoning; and Visual-SR1 Li et al. (2025b), which enhances step-by-step visual reasoning with self-refinement. This selection covers both state-of-the-art backbones and recent "thinking with images" algorithms for visual reasoning.

Table 1: Results on General VQA Benchmarks (accuracy, %). Δ indicates improvements of DeFacto over Qwen2.5-VL 7B.

Model	**Backbone**	VQAv2	OKVQA	GQA	SciQA	VizWiz	VSR
Qwen2.5-VL	Qwen2.5-VL-7B	57.3	54.5	41.3	85.3	37.7	2.2
ViCrop	LLaVA-1.5 (Vicuna-7B)	76.5	60.7	61.0	88.2	64.4	65.4
GRIT	Qwen2.5-VL-3B	71.5	55.4	59.3	60.5	46.3	61.0
DeepEyes	Qwen2.5-VL-7B	–	46.9	47.3	59.2	25.1	27.3
Visual-SR1	Qwen2.5-VL-7B	71.5	45.1	58.5	**88.6**	32.0	62.3
DeFacto (ours)	Qwen2.5-VL-7B	**79.7**	**68.0**	**70.1**	88.2	**64.5**	**70.3**
Δ (vs Qwen2.5-VL 7B)	–	+22.4	+13.5	+28.8	+2.9	+26.8	+68.1

Table 2: Results on Document VQA and Scene Text-centric Benchmarks (accuracy, %). Δ indicates improvements of DeFacto over Qwen2.5-VL 7B.

Model	**Document VQA**						**Scene Text-centric**		
	DocVQA	ChartQA	InfoVQA	DeepForm	KLC	WTQ	STVQA	TextVQA	AI2D
Qwen2.5-VL	84.4	77.8	66.0	30.3	35.9	63.9	64.9	71.0	71.2
GRIT	76.4	68.7	49.1	15.8	19.9	35.7	71.3	**73.4**	77.2
ViCrop	33.7	52.5	54.9	21.9	33.4	54.3	74.0	63.4	69.2
DeepEyes	66.8	44.4	42.3	–	33.1	54.6	48.9	39.9	38.5
Visual-SR1	82.3	73.8	75.1	**52.4**	**39.6**	72.2	60.2	69.2	71.5
DeFacto (ours)	**85.8**	**82.4**	**76.9**	51.8	37.6	**74.5**	**74.1**	**73.4**	**79.0**
Δ (vs Qwen2.5-VL 7B)	+1.4	+4.6	+10.9	+21.5	+1.7	+10.6	+9.2	+2.4	+7.8

Benchmarks. Our evaluation spans a diverse collection of visual reasoning benchmarks. For general-purpose VQA, we use OKVQA Marino et al. (2019), VQAv2 Goyal et al. (2017), GQA Hudson & Manning (2019), VizWiz Gurari et al. (2018), ScienceQA Lu et al. (2022) and VSR Liu et al. (2023). For document- and structure-centric evaluation, we adopt DocVQA Mathew et al. (2021), ChartQA Masry et al. (2022), InfoVQA Mathew et al. (2022), DeepForm Svetlichnaya (2020), Kleister KLC Stanisławek et al. (2021), and WikiTableQuestions (WTQ) Pasupat & Liang (2015). To test text-intensive reasoning, we include TextVQA Singh et al. (2019), AI2D Kembhavi et al. (2016) and STVQA Biten et al. (2019). We further evaluate on several benchmarks, including OCRBench Liu et al. (2024c), MMstar Chen et al. (2024a), MMMU Yue et al. (2024), and $\text{MMB}_{1.1}$ Liu et al. (2024b), with detailed results reported in Appendix E (Table 6).

Training Configuration. We train all models with the AdamW optimizer using a learning rate of 1×10^{-6}, $(\beta_1, \beta_2) = (0.9, 0.999)$, and $\epsilon = 1 \times 10^{-8}$. Training is performed with a global batch size of 8 and micro-batch size of 1 per GPU, combined with gradient accumulation steps of 2. Gradients are clipped to a maximum norm of 1.0 to ensure stability. We enable BF16 precision training. All experiments are conducted on 8 NVIDIA H100 GPUs with 80GB memory each, and models are trained for one epoch over the collected dataset.

4.2 Main Results

Results on General VQA Benchmarks. Table 1 compares DeFacto with recent visual reasoning and thinking with images baselines on six widely used benchmarks. DeFacto achieves state-of-the-art performance across the board, outperforming the strongest competing method, ViCrop, by clear margins. In particular, it improves over ViCrop by +3.2% on VQAv2, +7.3% on OKVQA, and +9.1% on GQA, demonstrating stronger compositional and commonsense reasoning. On perception-heavy datasets, DeFacto also shows advantages: it slightly surpasses Visual-SR1 on SciQA while matching ViCrop on VizWiz, and it exceeds all baselines on VSR by +4.9%, confirming its robustness under visually complex or noisy conditions. These consistent gains over the best-performing alternatives highlight the effectiveness of counterfactual training in enforcing evidence-grounded reasoning.

Performance on Document and Text-centric Benchmarks. As shown in Table 2, DeFacto also leads on document-style and scene text-centric benchmarks. It surpasses the strongest alter-

natives by notable margins, including +1.4% over Qwen2.5-VL on DocVQA, +4.6% on ChartQA, and +1.8% over Visual-SR1 on InfoVQA. On DeepForm, although Visual-SR1 achieves the best score, DEFACTO remains highly competitive with a close result of 51.8%. Similarly, while GRIT ties for the highest score on TextVQA, DEFACTO delivers the best overall performance across all text-centric tasks, including a +13.9% gain over Visual-SR1 on STVQA and a +1.8% improvement over GRIT on AI2D. These results confirm that DEFACTO not only consistently outperforms the strongest existing methods but also maintains competitive accuracy in the few cases where another baseline achieves the top result, establishing a new state of the art in document and OCR-centric reasoning tasks.

4.3 ABLATION STUDY

We compare four training settings on Qwen2.5-VL 7B. (i) **SFT (no CF)**: trained only on original data. (ii) **SFT (CF alignment)**: trained on original + counterfactual data, but counterfactuals are supervised only with the "Unknown" label, together with random-masking. (iii) **GRPO (no CF reward)**: GRPO training that uses only the first term of Eq. 6 (answer correctness) and the format reward, while removing the region-selection reward. (iv) **DeFacto (full)**: our complete framework with all three rewards.

Table 3: Ablation results on representative benchmarks (accuracy, %). Δ indicates improvements of DeFacto over baselines.

Model Variant	VQAv2	OKVQA	SciQA	VSR	DocVQA	TextVQA
Qwen2.5-VL (SFT, no CF)	61.2	42.0	82.7	54.5	51.9	56.0
Qwen2.5-VL (SFT, CF alignment)	66.5	55.7	84.7	53.7	84.3	73.0
Qwen2.5-VL (GRPO, no CF reward)	70.4	56.9	85.9	58.4	85.4	72.8
DeFacto (CF reward + GRPO)	**79.7**	**68.0**	**88.2**	**70.3**	**85.8**	**73.4**
Δ (vs GRPO no CF reward)	+9.3	+11.1	+2.3	+11.9	+0.4	+0.6

Effect of Counterfactual Supervision. The first two rows show that introducing counterfactual data with abstention alignment improves over standard SFT, with clear gains such as +5.3% on VQAv2 and +13.7% on OKVQA. This suggests that counterfactual supervision effectively reduces spurious correlations and strengthens evidence alignment.

Effect of Reinforcement Learning. GRPO without counterfactual rewards further boosts reasoning, e.g., +4.7% on VSR over SFT no CF. DeFacto achieves the best results overall, with additional gains of +9.3% on VQAv2, +11.1% on OKVQA, and +11.9% on VSR compared to GRPO. Even on DocVQA and TextVQA, improvements (+0.4%, +0.6%) remain consistent, confirming the importance of counterfactual rewards for robust, region-faithful reasoning.

5 CONCLUSION

In this work, we introduced *DeFacto*, the first vision-language reasoning framework explicitly grounded in counterfactual supervision, designed to enforce region-faithful reasoning and abstention behavior when critical evidence is missing. To enable this counterfactual reasoning paradigm, we proposed an automatic pipeline for constructing counterfactual datasets, which leverages language model parsing, open-vocabulary detection, and OCR to mask question-relevant regions without requiring manual annotations. Using this pipeline, we built a counterfactual dataset about 100k images to support training and evaluation. Extensive experiments across multiple diverse benchmarks demonstrate that DeFacto consistently improves both answer accuracy and visual grounding faithfulness over strong baselines. Our ablation studies further confirm the necessity of counterfactual training and region-level reward design in enhancing interpretability and robustness. We believe these findings open new directions for integrating counterfactual supervision into multimodal reasoning systems, with potential extensions to video understanding and embodied AI.

ETHICS STATEMENT

This work does not involve human subjects, sensitive personal data, or applications with foreseeable ethical risks. All experiments are conducted on publicly available benchmarks or our automatically constructed counterfactual dataset, which contains no personally identifiable information. We therefore believe this research poses no ethical concerns.

REPRODUCIBILITY STATEMENT

We have made every effort to ensure reproducibility of our results. The full training pipeline, including dataset construction, reward design, and reinforcement learning setup, is described in detail in the main paper and appendix. Our implementation is based on the open-source `open_r1` OpenAI (2025) repository, which we modified to incorporate our counterfactual dataset, reward functions, and GRPO training. The source code is provided in the supplementary materials to facilitate reproduction. Due to anonymity requirements and the large size of the dataset, we are unable to release the full dataset at this stage; however, it will be made publicly available upon acceptance. In the meantime, partial dataset visualizations are included in Appendix H to illustrate the construction process and provide qualitative insights.

REFERENCES

Ehsan Abbasnejad, Damien Teney, Amin Parvaneh, Javen Shi, and Anton van den Hengel. Counterfactual vision and language learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10044–10054, 2020.

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katherine Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *Advances in neural information processing systems*, 35:23716–23736, 2022.

Maximilian Augustin, Yannic Neuhaus, and Matthias Hein. Dig-in: Diffusion guidance for investigating networks-uncovering classifier differences neuron visualisations and visual counterfactual explanations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11093–11103, 2024.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, Humen Zhong, Yuanzhi Zhu, Mingkun Yang, Zhaohai Li, Jianqiang Wan, Pengfei Wang, Wei Ding, Zheren Fu, Yiheng Xu, Jiabo Ye, Xi Zhang, Tianbao Xie, Zesen Cheng, Hang Zhang, Zhibo Yang, Haiyang Xu, and Junyang Lin. Qwen2.5-vl technical report. *arXiv preprint arXiv:2502.13923*, 2025.

Ali Furkan Biten, Ruben Tito, Andres Mafla, Lluis Gomez, Marçal Rusinol, Ernest Valveny, CV Jawahar, and Dimosthenis Karatzas. Scene text visual question answering. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 4291–4301, 2019.

Meng Cao, Haoze Zhao, Can Zhang, Xiaojun Chang, Ian Reid, and Xiaodan Liang. Ground-r1: Incentivizing grounded visual reasoning via reinforcement learning. *arXiv preprint arXiv:2505.20272*, 2025.

Lin Chen, Jinsong Li, Xiaoyi Dong, Pan Zhang, Yuhang Zang, Zehui Chen, Haodong Duan, Jiaqi Wang, Yu Qiao, Dahua Lin, et al. Are we on the right way for evaluating large vision-language models? *arXiv preprint arXiv:2403.20330*, 2024a.

Wenhu Chen, Hongmin Wang, Jianshu Chen, Yunkai Zhang, Hong Wang, Shiyang Li, Xiyou Zhou, and William Yang Wang. Tabfact: A large-scale dataset for table-based fact verification. *arXiv preprint arXiv:1909.02164*, 2019.

Zhe Chen, Weiyun Wang, Hao Tian, Shenglong Ye, Zhangwei Gao, Erfei Cui, Wenwen Tong, Kongzhi Hu, Jiapeng Luo, Zheng Ma, et al. How far are we to gpt-4v? closing the gap to commercial multimodal models with open-source suites. *Science China Information Sciences*, 67 (12):220101, 2024b.

Zhe Chen, Jiannan Wu, Wenhai Wang, Weijie Su, Guo Chen, Sen Xing, Muyan Zhong, Qinglong Zhang, Xizhou Zhu, Lewei Lu, et al. Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 24185–24198, 2024c.

Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. *Advances in neural information processing systems*, 36:10088–10115, 2023.

Yue Fan, Xuehai He, Diji Yang, Kaizhi Zheng, Ching-Chen Kuo, Yuting Zheng, Sravana Jyothi Narayanaraju, Xinze Guan, and Xin Eric Wang. Grit: Teaching mllms to think with images. *arXiv preprint arXiv:2505.15879*, 2025.

Xingyu Fu, Minqian Liu, Zhengyuan Yang, John Corring, Yijuan Lu, Jianwei Yang, Dan Roth, Dinei Florencio, and Cha Zhang. Refocus: Visual editing as a chain of thought for structured image understanding. *arXiv preprint arXiv:2501.05452*, 2025.

Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 6904–6913, 2017.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Danna Gurari, Qing Li, Abigale J Stangl, Anhong Guo, Chi Lin, Kristen Grauman, Jiebo Luo, and Jeffrey P Bigham. Vizwiz grand challenge: Answering visual questions from blind people. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3608–3617, 2018.

Shengding Hu, Yuge Tu, Xu Han, Chaoqun He, Ganqu Cui, Xiang Long, Zhi Zheng, Yewei Fang, Yuxiang Huang, Weilin Zhao, et al. Minicpm: Unveiling the potential of small language models with scalable training strategies. *arXiv preprint arXiv:2404.06395*, 2024.

Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 6700–6709, 2019.

Noman Islam, Zeeshan Islam, and Nazia Noor. A survey on optical character recognition system. *arXiv preprint arXiv:1710.05703*, 2017.

Aniruddha Kembhavi, Mike Salvato, Eric Kolve, Minjoon Seo, Hannaneh Hajishirzi, and Ali Farhadi. A diagram is worth a dozen images. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14*, pp. 235–251. Springer, 2016.

Bo Li, Yuanhan Zhang, Dong Guo, Renrui Zhang, Feng Li, Hao Zhang, Kaichen Zhang, Peiyuan Zhang, Yanwei Li, Ziwei Liu, et al. Llava-onevision: Easy visual task transfer. *arXiv preprint arXiv:2408.03326*, 2024.

Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. In *International conference on machine learning*, pp. 19730–19742. PMLR, 2023.

Zhiqi Li, Guo Chen, Shilong Liu, Shihao Wang, Vibashan VS, Yishen Ji, Shiyi Lan, Hao Zhang, Yilin Zhao, Subhashree Radhakrishnan, et al. Eagle 2: Building post-training data strategies from scratch for frontier vision-language models. *arXiv preprint arXiv:2501.14818*, 2025a.

Zongxia Li, Wenhao Yu, Chengsong Huang, Rui Liu, Zhenwen Liang, Fuxiao Liu, Jingxi Che, Dian Yu, Jordan Boyd-Graber, Haitao Mi, et al. Self-rewarding vision-language model via reasoning decomposition. *arXiv preprint arXiv:2508.19652*, 2025b.

Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *Advances in neural information processing systems*, 36:34892–34916, 2023.

Haotian Liu, Chunyuan Li, Yuheng Li, and Yong Jae Lee. Improved baselines with visual instruction tuning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 26296–26306, 2024a.

Yuan Liu, Haodong Duan, Yuanhan Zhang, Bo Li, Songyang Zhang, Wangbo Zhao, Yike Yuan, Jiaqi Wang, Conghui He, Ziwei Liu, et al. Mmbench: Is your multi-modal model an all-around player? In *European conference on computer vision*, pp. 216–233. Springer, 2024b.

Yuliang Liu, Zhang Li, Mingxin Huang, Biao Yang, Wenwen Yu, Chunyuan Li, Xu-Cheng Yin, Cheng-Lin Liu, Lianwen Jin, and Xiang Bai. Ocrbench: on the hidden mystery of ocr in large multimodal models. *Science China Information Sciences*, 67(12):220102, 2024c.

Yuqi Liu, Tianyuan Qu, Zhisheng Zhong, Bohao Peng, Shu Liu, Bei Yu, and Jiaya Jia. Vision-reasoner: Unified visual perception and reasoning via reinforcement learning. *arXiv preprint arXiv:2505.12081*, 2025a.

Ziyu Liu, Zeyi Sun, Yuhang Zang, Xiaoyi Dong, Yuhang Cao, Haodong Duan, Dahua Lin, and Jiaqi Wang. Visual-rft: Visual reinforcement fine-tuning. *arXiv preprint arXiv:2503.01785*, 2025b.

Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. *Advances in Neural Information Processing Systems*, 35:2507–2521, 2022.

Kenneth Marino, Mohammad Rastegari, Ali Farhadi, and Roozbeh Mottaghi. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Proceedings of the IEEE/cvf conference on computer vision and pattern recognition*, pp. 3195–3204, 2019.

Ahmed Masry, Do Xuan Long, Jia Qing Tan, Shafiq Joty, and Enamul Hoque. Chartqa: A benchmark for question answering about charts with visual and logical reasoning. *arXiv preprint arXiv:2203.10244*, 2022.

Minesh Mathew, Dimosthenis Karatzas, and CV Jawahar. Docvqa: A dataset for vqa on document images. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, pp. 2200–2209, 2021.

Minesh Mathew, Viraj Bagal, Rubèn Tito, Dimosthenis Karatzas, Ernest Valveny, and CV Jawahar. Infographicvqa. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 1697–1706, 2022.

Microsoft. Introducing gpt-4o-2024-08-06 api with structured outputs on azure. `https://techcommunity.microsoft.com/blog/azure-ai-services-blog/introducing-gpt-4o-2024-08-06-api-with-structured-outputs-on-azure/4232684`, 2024. Accessed: 2025-03-07.

Anand Mishra, Shashank Shekhar, Ajeet Kumar Singh, and Anirban Chakraborty. Ocr-vqa: Visual question answering by reading text in images. In *ICDAR*, 2019.

Yulei Niu, Kaihua Tang, Hanwang Zhang, Zhiwu Lu, Xian-Sheng Hua, and Ji-Rong Wen. Counterfactual vqa: A cause-effect look at language bias. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 12700–12710, 2021.

OpenAI. Thinking with images, 2025. URL https://openai.com/index/thinking-with-images/. Accessed: 2025-08-06.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in neural information processing systems*, 35: 27730–27744, 2022.

Panupong Pasupat and Percy Liang. Compositional semantic parsing on semi-structured tables. *arXiv preprint arXiv:1508.00305*, 2015.

Maitreya Patel, Tejas Gokhale, Chitta Baral, and Yezhou Yang. Cripp-vqa: Counterfactual reasoning about implicit physical properties via video question answering. *arXiv preprint arXiv:2211.03779*, 2022.

Zhiliang Peng, Wenhui Wang, Li Dong, Yaru Hao, Shaohan Huang, Shuming Ma, and Furu Wei. Kosmos-2: Grounding multimodal large language models to the world. *arXiv preprint arXiv:2306.14824*, 2023.

Ji Qi, Ming Ding, Weihan Wang, Yushi Bai, Qingsong Lv, Wenyi Hong, Bin Xu, Lei Hou, Juanzi Li, Yuxiao Dong, et al. Cogcom: A visual language model with chain-of-manipulations reasoning. *arXiv preprint arXiv:2402.04236*, 2024.

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28, 2015.

Tianhe Ren, Yihao Chen, Qing Jiang, Zhaoyang Zeng, Yuda Xiong, Wenlong Liu, Zhengyu Ma, Junyi Shen, Yuan Gao, Xiaoke Jiang, Xingyu Chen, Zhuheng Song, Yuhong Zhang, Hongjie Huang, Han Gao, Shilong Liu, Hao Zhang, Feng Li, Kent Yu, and Lei Zhang. Dino-x: A unified vision model for open-world object detection and understanding, 2024. URL https://arxiv.org/abs/2411.14347.

Hao Shao, Shengju Qian, Han Xiao, Guanglu Song, Zhuofan Zong, Letian Wang, Yu Liu, and Hongsheng Li. Visual cot: Advancing multi-modal language models with a comprehensive dataset and benchmark for chain-of-thought reasoning. *Advances in Neural Information Processing Systems*, 37:8612–8642, 2024.

Amanpreet Singh, Vivek Natarajan, Meet Shah, Yu Jiang, Xinlei Chen, Dhruv Batra, Devi Parikh, and Marcus Rohrbach. Towards vqa models that can read. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 8317–8326, 2019.

Tomasz Stanisławek, Filip Graliński, Anna Wróblewska, Dawid Lipiński, Agnieszka Kaliska, Paulina Rosalska, Bartosz Topolski, and Przemysław Biecek. Kleister: key information extraction datasets involving long documents with complex layouts. In *International Conference on Document Analysis and Recognition*, pp. 564–579. Springer, 2021.

Guangyan Sun, Mingyu Jin, Zhenting Wang, Cheng-Long Wang, Siqi Ma, Qifan Wang, Tong Geng, Ying Nian Wu, Yongfeng Zhang, and Dongfang Liu. Visual agents as fast and slow thinkers. *arXiv preprint arXiv:2408.08862*, 2024.

S Svetlichnaya. Deepform: Understand structured documents at scale. 2020.

Ryota Tanaka, Kyosuke Nishida, and Sen Yoshida. Visualmrc: Machine reading comprehension on document images. In *AAAI*, 2021.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, Katie Millican, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

Gemini Team, Petko Georgiev, Ving Ian Lei, Ryan Burnell, Libin Bai, Anmol Gulati, Garrett Tanzer, Damien Vincent, Zhufeng Pan, Shibo Wang, et al. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context. *arXiv preprint arXiv:2403.05530*, 2024.

OpenAI Team. Gpt-4v (ision) system card. 2023. *URL https://api. semanticscholar. org/CorpusID*, 263218031.

OpenGVLab Team. Internvl2: Better than the best—expanding performance boundaries of open-source multimodal models with the progressive scaling strategy, 2024.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Xue Wang, Zhibo Wang, Haiqin Weng, Hengchang Guo, Zhifei Zhang, Lu Jin, Tao Wei, and Kui Ren. Counterfactual-based saliency map: Towards visual contrastive explanations for neural networks. In *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 2042–2051, 2023.

Penghao Wu and Saining Xie. V?: Guided visual search as a core mechanism in multimodal llms. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 13084–13094, 2024.

Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruoqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, et al. Mmmu: A massive multi-discipline multimodal understanding and reasoning benchmark for expert agi. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 9556–9567, 2024.

Jianrui Zhang, Mu Cai, Tengyang Xie, and Yong Jae Lee. Countercurate: Enhancing physical and semantic visio-linguistic compositional reasoning via counterfactual examples. *arXiv preprint arXiv:2402.13254*, 2024a.

Jiarui Zhang, Mahyar Khayatkhoei, Prateek Chhikara, and Filip Ilievski. Mllms know where to look: Training-free perception of small visual details with multimodal llms. *arXiv preprint arXiv:2502.17422*, 2025a.

Letian Zhang, Xiaotong Zhai, Zhongkai Zhao, Yongshuo Zong, Xin Wen, and Bingchen Zhao. What if the tv was off? examining counterfactual reasoning abilities of multi-modal language models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 21853–21862, 2024b.

Xintong Zhang, Zhi Gao, Bofei Zhang, Pengxiang Li, Xiaowen Zhang, Yang Liu, Tao Yuan, Yuwei Wu, Yunde Jia, Song-Chun Zhu, et al. Chain-of-focus: Adaptive visual search and zooming for multimodal reasoning via rl. *arXiv preprint arXiv:2505.15436*, 2025b.

Yifeng Zhang, Ming Jiang, and Qi Zhao. Learning chain of counterfactual thought for bias-robust vision-language reasoning. In *European Conference on Computer Vision*, pp. 334–351. Springer, 2024c.

Zhu Zhang, Zhou Zhao, Zhijie Lin, Xiuqiang He, et al. Counterfactual contrastive learning for weakly-supervised vision-language grounding. *Advances in Neural Information Processing Systems*, 33:18123–18134, 2020.

Ziwei Zheng, Michael Yang, Jack Hong, Chenxiao Zhao, Guohai Xu, Le Yang, Chao Shen, and Xing Yu. Deepeyes: Incentivizing" thinking with images" via reinforcement learning. *arXiv preprint arXiv:2505.14362*, 2025.

Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.

Shiding Zhu, Wenhui Dong, Jun Song, Yingbo Wang, Yanan Guo, and Bo Zheng. Hyvilm: Enhancing fine-grained recognition with a hybrid encoder for vision-language models. *arXiv preprint arXiv:2412.08378*, 2024.

APPENDIX A. SYSTEM PROMPT EXAMPLE

System Prompt

```
Please answer my question based on the image I have provided. Identify the region in the
image that is most relevant to the question and provide bounding box coordinates.
Output requirements:
1. The bounding boxes must be wrapped in <bbox> ... </bbox> tags.
2. The thinking process must be wrapped in <think> ... </think> tags.
3. The final answer must be wrapped in <answer> ... </answer> tags.
Format of the response (must strictly follow this structure): <bbox>['Position': [x1, y1,
x2, y2], 'Confidence': number] </bbox> <think> ... </think> <answer>...</answer>
The current question is:
```

APPENDIX B.TRAINING CONFIGURATION DETAILS

Table 4 summarizes the key hyperparameters used in our experiments.

Table 4: Training configuration.

Parameter	Value
Optimizer	AdamW
Learning rate	1×10^{-6}
Adam betas	(0.9, 0.999)
Adam ϵ	1×10^{-8}
Weight decay	0.0
Precision	BF16 (FP16 disabled)
Batch size (global)	8
Micro batch size / GPU	1
Gradient accumulation steps	2
Gradient clipping	1.0
ZeRO optimization	Stage 3 with CPU offloading
Overlap communication	Enabled
Pinned memory	Enabled
Steps per print	inf
Wall clock breakdown	False
Hardware	8 $\times$ NVIDIA H100 (80GB)
Epochs	1

APPENDIX C. PROMPT FOR EVALUATION

During evaluation, we employed `Qwen3` as the judge model to score the generated answers. The following prompt was used to guide the evaluation process:

Evaluation Prompt

```
"prompt": "Human: You are responsible for proofreading the answers, you need to give
a score to the model's answer by referring to the standard answer, based on the given
question. The full score is 1 point and the minimum score is 0 points. Please output the
score in the format "<score>". The evaluation criteria require that the closer the model's
answer is to the standard answer, the higher the score. Note that the standard answer may
be a list containing multiple possible correct answers."
```

APPENDIX D. REWARD HYPERPARAMETERS

Table 5 reports the hyperparameter settings used in our reward design (Eq. 5). These values were tuned to balance the contributions of the three reward components: answer correctness (R_{ans}), format consistency (R_{fmt}), and region selection coherence (R_{sel}). The settings reflect the following intuition: γ_{corr} is set larger than γ_{guess} to penalize counterfactual "lucky guesses" more severely, ρ_{unk} rewards correct abstentions in counterfactual cases, and β_{pos} is emphasized to encourage stronger

alignment with evidence regions in positive/random cases. Together with the weighting (λ_1, λ_2), these hyperparameters yield the reward dynamics shown in Fig. 3.

Table 5: Reward hyperparameter settings for the composite reward in Eq. 5.

Component	Parameter	Value
Answer Correctness (R_{ans})	γ_{unk}	0.2
	ρ_{unk}	1.0
	γ_{guess}	0.8
	γ_{corr}	1.0
Format Consistency (R_{fmt})	α	1.0
Region Selection (R_{sel})	β_{pos}	1.0
	β_{neg}	0.6
	$\gamma_{\varnothing}$	0.5
Composite Reward	(λ_1, λ_2)	$(0.3,\ 0.5)$

APPENDIX E. ADDITIONAL RESULTS

Table 6 provides an extended comparison of *DeFacto* with both closed-source and publicly available vision-language models on additional benchmarks, including **OCRBench**, **MMstar**, **MMMU**, and **MMB$_{1.1}$**. As shown, DeFacto achieves the best score on OCRBench (871) and competitive performance across the remaining three benchmarks. In particular, our method surpasses most open-source models by a clear margin and remains close to strong closed-source systems such as GPT-4o, while slightly improving over Eagle2-9B on OCRBench. These results further demonstrate that DeFacto effectively balances answer accuracy and reasoning faithfulness, yielding robust gains across diverse evaluation settings.

Table 6: Comparison with SoTA models on Various Benchmarks.

Model	OCRBench	MMstar	MMMU	MMB$_{1.1}$
Closed-Source Models				
GPT-4o-0513 Microsoft (2024)	736	**63.9**	**69.2**	**82.2**
GPT-4V Team	656	56.0	61.7	79.8
Gemini-1.5-Pro Team et al. (2024)	754	-	62.2	-
Publicly Available Models				
LLaVa-OneVision-0.5B Li et al. (2024)	565	37.7	31.4	50.3
InternVL2-1B Team (2024)	754	45.7	36.7	59.7
Eagle2-1B Li et al. (2025a)	767	48.5	38.8	63.0
InternVL2-2B Team (2024)	784	50.1	36.3	69.6
Eagle2-2B Li et al. (2025a)	818	56.4	43.1	74.9
InternVL2-8B Team (2024)	794	60.9	51.8	79.4
MiniCPM-V2.6 Hu et al. (2024)	852	57.5	49.8	78.0
LLaVA-One-Vision-7B Li et al. (2024)	622	61.7	48.8	80.9
InternVL2-26B Team (2024)	825	61.0	50.7	81.2
LLaMa-3.2-90B-Vision Grattafiori et al. (2024)	783	55.3	60.3	77.3
HyViLMZhu et al. (2024)	596	-	41.8	76.6
Eagle2-9B Li et al. (2025a)	868	62.6	56.1	80.6
DeFacto-7B (ours)	**871**	63.2	66.0	81.2

APPENDIX F. LIMITATIONS

While *DeFacto* demonstrates consistent improvements in answer accuracy and reasoning faithfulness, there are a few limitations to note. First, our current implementation relies on publicly available

detectors (e.g., RPN, OCR, and open-vocabulary models) for region proposal, which may introduce occasional errors or inefficiencies; however, this can be alleviated as stronger detectors become available. Second, our counterfactual dataset consists about 100k images, which is sufficient for controlled experiments but still modest compared to large-scale pretraining corpora. Lastly, our framework has so far been evaluated on static images, leaving the extension to videos and temporal reasoning as an open direction for future work.

APPENDIX G. BROADER IMPACT

Our work promotes safer and more interpretable multimodal reasoning by ensuring that models align their predictions with visual evidence. Beyond algorithmic contributions, we release a large-scale counterfactual dataset of about 100k images, which we believe will be a valuable resource for the community to study faithful reasoning.

APPENDIX H. VISUALIZATION OF COUNTERFACTUAL DATASET

In this section, we provide visualizations of the constructed counterfactual dataset. Each sample consists of three views:

(a) Original: the original unmodified image.

(b) Original_smask: the image with task-relevant (key) regions masked out.

(c) Original_rmask: the image with task-irrelevant regions masked out. Figures 4–19 show representative examples from the dataset.

Question: What type of boat is this? Answer:

Answer: barge

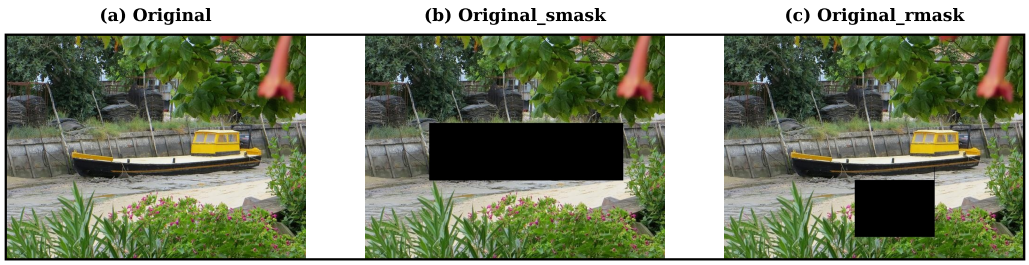

Figure 4: Visualization Example 1

Question: What is the red line represents? Answer:

Answer: Share of women who prefer a male boss

(a) Original **(b) Original_smask** **(c) Original_rmask**

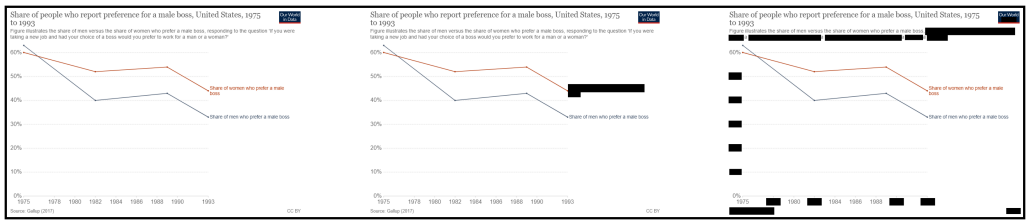

Figure 5: Visualization Example 2

Question: Which kind of food is to the left of the fork? Answer:

Answer: salad

(a) Original **(b) Original_smask** **(c) Original_rmask**

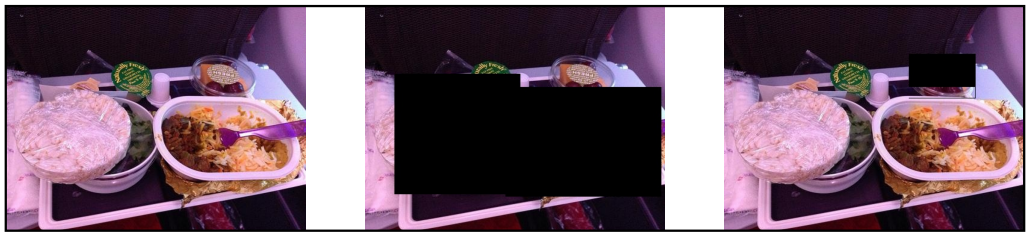

Figure 6: Visualization Example 3

Question: What is the water in front of? Answer:

Answer: trees

(a) Original **(b) Original_smask** **(c) Original_rmask**

Figure 7: Visualization Example 4

Question: What is the frame made of? Answer:

Answer: wood

Figure 8: Visualization Example 5

Question: Is the truck parked straight on a driveway? Answer:

Answer: no

Figure 9: Visualization Example 6

Question: Which kind of animal is standing on the hay? Answer:

Answer: cow

Figure 10: Visualization Example 7

Question: What is the total direct enterprise investment of Ireland (in euros) in start-ups in 2015? Answer:

Answer: 31m

(a) Original **(b) Original_smask** **(c) Original_rmask**

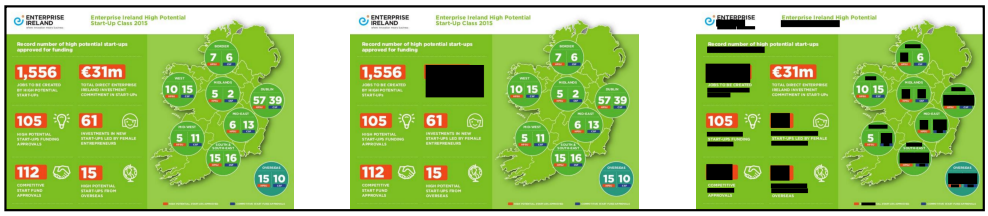

Figure 11: Visualization Example 8

Question: what is the name of the wine? Answer:

Answer: italica

(a) Original **(b) Original_smask** **(c) Original_rmask**

Figure 12: Visualization Example 9

Question: Who is wearing a vest? Answer:

Answer: woman

(a) Original **(b) Original_smask** **(c) Original_rmask**

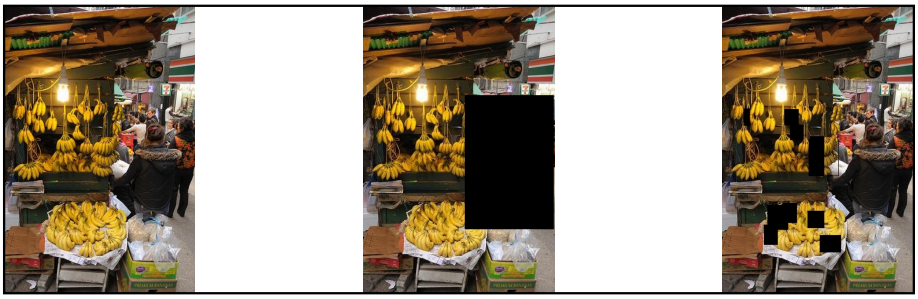

Figure 13: Visualization Example 10

Question: what number gate is this? Answer:

Answer: 97

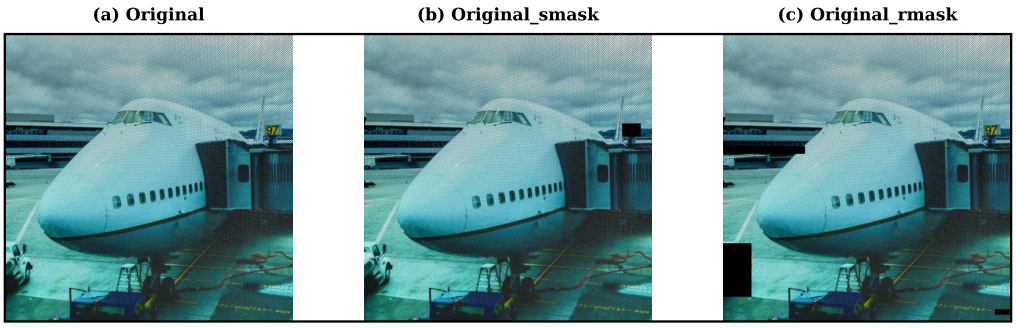

Figure 14: Visualization Example 11

Question: where is this bus going? Answer:

Answer: 8mt st vincent

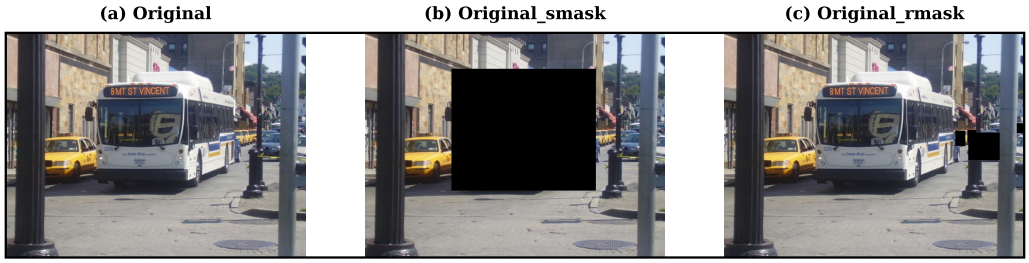

Figure 15: Visualization Example 12

Question: What color is the bag? Answer:

Answer: green

Figure 16: Visualization Example 13

Question: What was the GDP per capita in Madagascar in 2020? Answer:

Answer: 501.76

(a) Original **(b) Original_smask** **(c) Original_rmask**

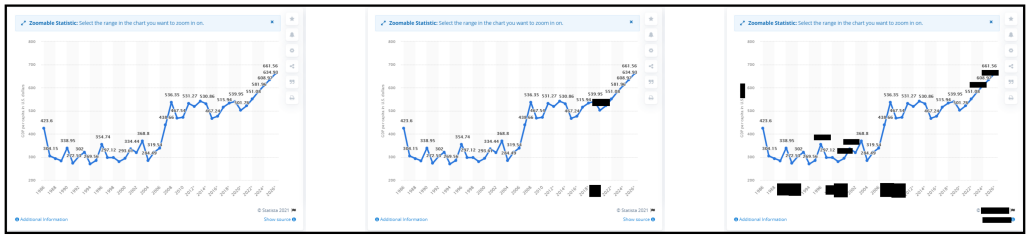

Figure 17: Visualization Example 14

Question: What company had a share of 16.5 percent of the world liner fleet? Answer:

Answer: Mediterranean Shg Co

(a) Original **(b) Original_smask** **(c) Original_rmask**

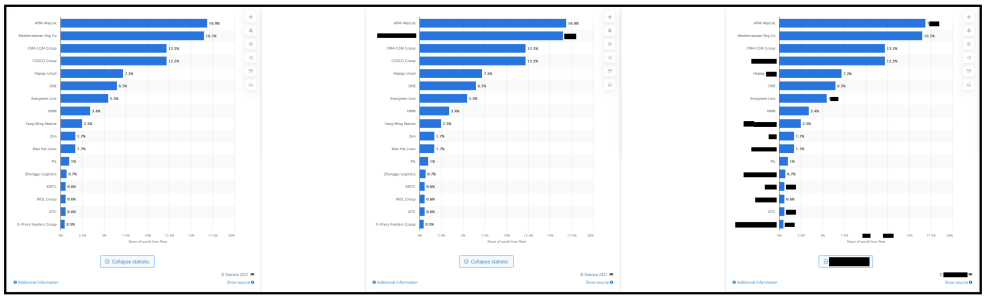

Figure 18: Visualization Example 15

Question: What hairstyle does the woman have? Answer:

Answer: ponytail

(a) Original **(b) Original_smask** **(c) Original_rmask**

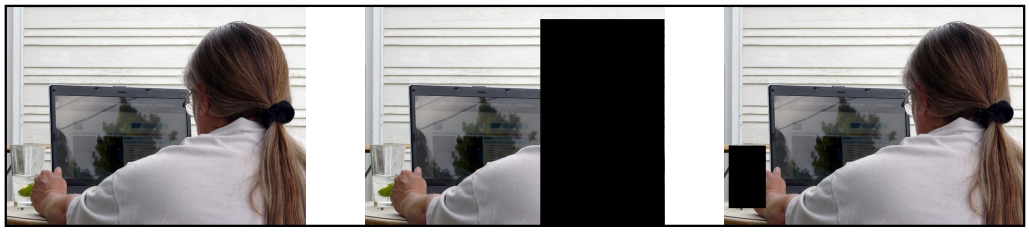

Figure 19: Visualization Example 16

APPENDIX H. THE USE OF LARGE LANGUAGE MODELS (LLMS)

In this work, we employed LLMs in a limited capacity to support writing and presentation. Specifically, we used an LLM to help with linguistic refinement in the *Introduction* and *Related Work* sections, ensuring clarity and fluency of exposition. In addition, we used LLM assistance for formatting tasks in the *Method* and *Experiment* sections, such as rendering mathematical formulas into standard LaTeX notation and typesetting tables in the appropriate style. All core research contributions, including algorithm design, dataset construction, experimental execution, and analysis, were entirely conducted by the authors without LLM involvement.