VISTA: VIEW-CONSISTENT SELF-VERIFIED TRAINING FOR GUI GROUNDING

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ABSTRACT

When applying Group Relative Policy Optimization (GRPO) for GUI Grounding, rollouts are sampled from a single screenshot view; groups often become either all failures on difficult instances or all successes on easy ones, yielding no useful relative advantage. We propose **VISTA** (**View-Consistent Self-Verified Training**), a GRPO-based training framework that constructs each comparison group from multiple target-preserving views of the same GUI instance. Each view is generated by a crop that keeps the target element visible and remaps its box exactly, so model rollouts are compared across semantically equivalent but geometrically different inputs. To stabilize short coordinate generation without turning reinforcement learning into unconditional imitation, VISTA further adds a self-verified cross-view anchor: an oracle answer optimized with an advantage-weighted loss, excluded from the group baseline and activated only when the model has produced a maximum-reward rollout. Across five GUI-grounding benchmarks and multiple Qwen backbones, VISTA consistently improves grounding accuracy. On ScreenSpot-Pro, it raises Qwen3-VL 4B/8B/30B-A3B from 55.5/52.7/53.7 to 63.4/65.8/67.0. Robustness analyses further show higher worst-view accuracy and lower prediction flip rates.

1 INTRODUCTION

GUI grounding enables autonomous agents to interact with digital interfaces by mapping a screenshot and a natural language instruction to a click coordinate (Wang et al., 2025a; Zhou et al., 2025a; Gu et al., 2025a; Wang et al., 2025c). Compared with general visual grounding, GUI grounding is especially sensitive to localization errors, as UI elements such as icons, input fields, and buttons are often small, densely arranged, and visually similar; a slight spatial mistake may activate the wrong element and disrupt the subsequent workflow (Tang et al., 2025b; Wang et al., 2025b).

Recent work has made significant progress in applying Group Relative Policy Optimization (GRPO) with verifiable rewards for GUI grounding, where click correctness can be evaluated by a rule-based *point-in-box* reward (Yang et al., 2025; Luo et al., 2025; Tang et al., 2025a).

However, as illustrated in Figure 1, directly applying GRPO to GUI grounding exposes two forms of reward degeneracy, both of which collapse the group-relative advantage and remove the learning signal (Guo et al., 2025; Yu et al., 2026; Lu et al., 2025). With sparse binary *point in box* rewards, repeated rollouts from a single view may all miss the target on difficult screenshots, forming a *fixed view all fail group*. On easier screenshots, all rollouts may hit the target, which also eliminates reward variance. Figure 3f shows that fewer than 5% of fixed-view training samples form informative groups, namely groups that are neither all-zero nor all-one. This issue is severe in GUI grounding because coordinates are tied to the screenshot geometry: a prediction that is correct in one view may shift after a target preserving crop, even when the target remains visible (see Table 5) (Zhang et al., 2025c). Thus, both all-fail and all-correct degeneracy reveal a shared bottleneck: vanilla GRPO constructs groups by repeatedly sampling from one fixed view, which often fails to expose informative differences among rollouts.

These observations suggest that the key design choice is not only how to reward a click, but also how to construct the comparison group. For GUI grounding, an informative group should preserve the same instruction and target semantics while varying the view geometry, so that the policy is compared across semantically equivalent but geometrically different inputs. Such view consistent

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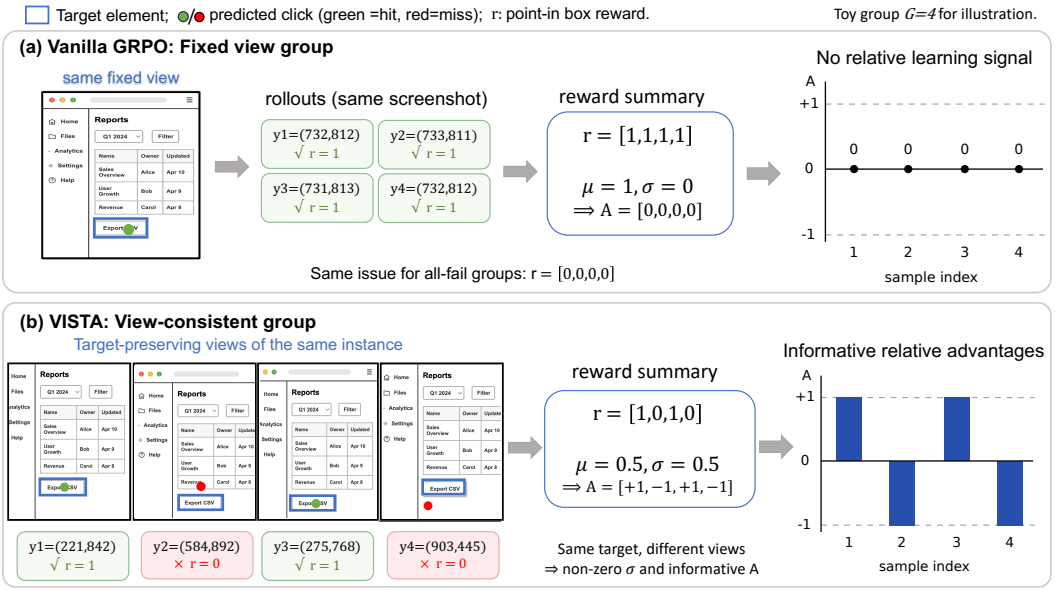


Figure 1: **Motivation of VISTA.** In vanilla GRPO, multiple rollouts from the same screenshot can produce homogeneous rewards, yielding zero relative advantage. VISTA constructs the group from target-preserving views of the same GUI instance. These views preserve the instruction and target semantics while changing the screenshot geometry. As a result, VISTA turns homogeneous fixed-view rewards into informative cross-view variation.

grouping increases the chance of observing a successful rollout on difficult instances and reveals unstable predictions on easy ones. By keeping the instruction and target unchanged while varying the view geometry, the policy is compared across inputs that require the same action but different coordinate predictions. Since coordinate generation is sensitive to format and geometry, we separate the model generated rollouts used for group statistics from the oracle answer, which is used only as a conditional stabilizing signal after the model has already succeeded.

In this work, we introduce VISTA (**View-Consistent Self-Verified Training**), a GRPO-based training framework for GUI grounding that revisits group construction from this perspective. VISTA consists of two components: **View-Consistent Group Rollout** and **Self-Verified Cross-View Anchoring**. View-Consistent Group Rollout constructs each GRPO group from multiple target-preserving views of the same GUI instance, rather than from repeated completions on a single screenshot. As shown in Figure 3f, this construction increases the fraction of informative groups, namely groups that are neither all-zero nor all-one, from fewer than 5% under fixed-view GRPO to around 20%, restoring useful intra-group reward variance for both difficult and easy instances. Thus, VISTA mitigates all-fail degeneracy primarily through view-consistent group construction, not through unconditional oracle injection.

However, multi-view rollout alone can make coordinate generation unstable on hard or ambiguous views. To stabilize training, we further introduce a self-verified cross-view anchor that uses oracle answers only as a conditional stabilizing signal, while keeping the GRPO comparison statistics defined by model-generated rollouts.

Our contributions are summarized as follows:

- We propose view-consistent group rollout, which constructs GRPO groups from multiple target-preserving views of the same GUI grounding instance and computes model-only group statistics across these views.
- We introduce a self-verified cross-view anchor that provides an oracle coordinate only when the current policy has already produced a maximum-reward rollout, preventing oracle targets from changing the GRPO baseline or supervising all-fail groups.
- We provide comprehensive validation across model family and benchmarks. On ScreenSpot-Pro, VISTA improves Qwen3-VL series models from 55.5/52.7/53.7 to 63.4/65.8/67.0 at the 4B/8B/30B-A3B scales.

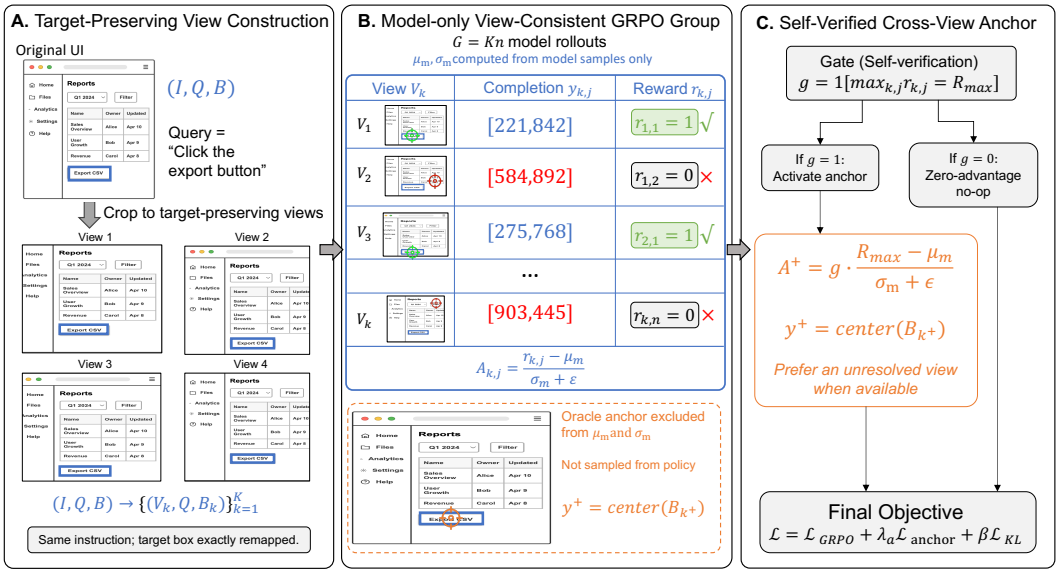


Figure 2: **Overview of VISTA.** VISTA constructs GRPO groups from target-preserving views of the same GUI grounding instance. Model rollouts define the group statistics, while an oracle-format center-point anchor is activated only for self-verified groups.

2 Related Work

GUI Grounding Recent advances in GUI agents have been driven by specialized GUI grounding models that map natural-language instructions to precise screen coordinates Tang et al. (2025b); Zhang et al. (2025a); Zheng et al. (2024); Wang et al. (2025b); Nguyen et al. (2025). Early works established the task through large-scale supervised fine-tuning (SFT) on GUI datasets, demonstrating effectiveness across mobile, web, and desktop interfaces Cheng et al. (2024); Lin et al. (2024); Qin et al. (2025b); Yang et al. (2024); Gou et al. (2025); Wu et al. (2024); Lu et al. (2024); Xu et al. (2025). More recently, reinforcement learning with rule-based click rewards has emerged as a promising technique to further enhance grounding accuracy beyond SFT baselines Yang et al. (2025); Tang et al. (2025a); Zhou et al. (2025b); Luo et al. (2025); Gu et al. (2025a); Team et al. (2026); Qiu et al. (2026). However, existing RL approaches suffer from diminishing training effectiveness as optimization progresses.

Oracle Guidance in GRPO Training GRPO has been widely adopted for post-training large language models, consistently improving performance across diverse tasks Yu et al. (2026); Guo et al. (2025); Shao et al. (2024). However, GRPO degenerates when group rollouts are uniformly correct or incorrect, collapsing the relative advantage to zero and eliminating the learning signal. To address this, recent works in math and reasoning try to introduce oracle guidance to ensure informative training updates. LUFFY Yan et al. (2026) mixes off-policy traces from a stronger teacher into the group, using regularized importance sampling to balance imitation and on-policy exploration. BREAD Zhang et al. (2026) adaptively inserts partial expert prefixes whenever on-policy rollouts fail, guaranteeing at least one successful trace per update.

3 Method

VISTA (**View-Consistent Self-Verified Training**) extends GRPO for GUI grounding with two components: rollout groups spanning target-preserving views and a conditional oracle anchor (Figure 2).

3.1 Problem Setup

Given a screenshot I, an instruction q, and a ground-truth target box $B = (x_1, y_1, x_2, y_2)$, GUI grounding asks a policy π_θ to output a coordinate string y. Following the Qwen-style grounding

interface, the output string y is parsed into a click point $\hat{\mathbf{p}} = (\hat{x}, \hat{y})$ in the discrete 0–1000 image coordinate space. Let $\mathrm{ValidFmt}(y)$ indicate whether y can be parsed as a coordinate string of the form `[x,y]`, and express B in the same normalized coordinate frame. We assign a binary reward for a valid click inside the target box:

$$R(y, B) = \mathbb{I}[\mathrm{ValidFmt}(y)] \cdot \mathbb{I}[\hat{\mathbf{p}} \in B]\,. \tag{1}$$

The maximum reward is therefore $R_{\max} = 1$.

3.2 GRPO FOR GUI GROUNDING

Standard GRPO (Guo et al., 2025) samples G completions $\{y_i\}_{i=1}^{G}$ for the same prompt and computes normalized advantages from the group rewards:

$$\begin{aligned} \mu_G &= \frac{1}{G}\sum_{i=1}^{G} r_i, \sigma_G = \sqrt{\frac{1}{G}\sum_{i=1}^{G}(r_i - \mu_G)^2}, \\ A_i &= \frac{r_i - \mu_G}{\sigma_G + \epsilon}. \end{aligned} \tag{2}$$

With binary grounding rewards, groups in which all rollouts succeed or all fail have zero relative advantage. We modify group construction to sample across views of the same grounding instance.

3.3 VIEW-CONSISTENT GROUP ROLLOUT

With probability p_{crop}, we construct K cropped views that fully contain the target, retain the instruction q, and remap the target coordinates to each view. Otherwise, we sample G completions from the original screenshot, equivalent to setting $K = 1$. View consistency refers to the shared target and exact coordinate remapping; we do not impose a separate prediction-consistency loss.

Target-preserving crop generation. Let the original image size be $W \times H$, and let $B^{\mathrm{px}} = (x_1, y_1, x_2, y_2)$ denote the target box in pixel coordinates. For each cropped view k, the initial crop size is set to $(w_k, h_k) = (0.9W,\, 0.9H)$. If the resulting crop is smaller than the target box, we enlarge it so that the target can be fully contained.

A valid crop window $C_k = (l_k, t_k, w_k, h_k)$ must satisfy $B^{\mathrm{px}} \subseteq C_k$. For each view, we independently sample the top-left corner uniformly from these feasible ranges:

$$\begin{aligned} l_k &\sim \mathcal{U}\left(\max(0, x_2 - w_k),\, \min(x_1, W - w_k)\right), \\ t_k &\sim \mathcal{U}\left(\max(0, y_2 - h_k),\, \min(y_1, H - h_k)\right), \end{aligned} \tag{3}$$

for $k = 1, \ldots, K$.

Coordinate remapping. For each valid crop, we remap the target box into the cropped coordinate frame and normalize it:

$$\begin{aligned} B_k = \big(&1000\tfrac{x_1 - l_k}{w_k}, 1000\tfrac{y_1 - t_k}{h_k}, \\ &1000\tfrac{x_2 - l_k}{w_k}, 1000\tfrac{y_2 - t_k}{h_k}\big). \end{aligned} \tag{4}$$

The cropped image is then resized for the VLM input; the normalized box coordinates remain unchanged by this resizing.

Group construction. Given K target-preserving views $\{(V_k, B_k)\}_{k=1}^{K}$, we sample $n = G/K$ completions per view, assuming K divides the GRPO group size G:

$$\begin{aligned} &y_{k,j} \sim \pi_{\theta_{\mathrm{old}}}(\cdot \mid V_k, q), \\ &r_{k,j} = R(y_{k,j}, B_k), \end{aligned} \quad k = 1, \ldots, K,\ j = 1, \ldots, n. \tag{5}$$

The model-generated group contains $G = Kn$ rollouts. Its statistics are computed as

$$\mu_{\mathrm{m}} = \frac{1}{G}\sum_{k=1}^{K}\sum_{j=1}^{n} r_{k,j},$$
$$\sigma_{\mathrm{m}} = \sqrt{\frac{1}{G}\sum_{k=1}^{K}\sum_{j=1}^{n}(r_{k,j}-\mu_{\mathrm{m}})^2}, \tag{6}$$

and the corresponding model-sample advantages are

$$A_{k,j} = \frac{r_{k,j}-\mu_{\mathrm{m}}}{\sigma_{\mathrm{m}}+\epsilon}. \tag{7}$$

Setting $K = G$ gives one completion per view; $n > 1$ allows multiple completions from each view.

3.4 Self-Verified Cross-View Anchoring

Multi-view rollout alone exhibits coordinate-format instability in our training diagnostics (Figure 3). We add an oracle coordinate anchor whose weight depends on the model-generated rewards. We call a group *self-verified* when at least one model rollout achieves $R_{\max}$ under the ground-truth verifier.

Let $\mathcal{P} = \{(k,j) : r_{k,j} = R_{\max}\}$ denote the set of maximum-reward model rollouts, and let $\mathcal{N}$ be its complement within the group. When $\mathcal{N}$ is non-empty, we sample a rollout index (k^+, j^+) uniformly from $\mathcal{N}$ and use its view for the anchor. Otherwise, we sample an index uniformly from the full group. When active, the anchor thus supervises a view with an unsuccessful rollout, conditioned on success elsewhere in the group.

Given the selected view V_{k^+} and its remapped box $B_{k^+} = (x_1, y_1, x_2, y_2)$, we construct the oracle-format coordinate sequence as the box center, $y^+ = \texttt{[}\lfloor (x_1+x_2)/2 \rfloor,\ \lfloor (y_1+y_2)/2 \rfloor\texttt{]}$.

The anchor advantage uses the model-only group statistics and a self-verification gate:

$$A^+ = \mathbb{I}[\mathcal{P} \neq \emptyset]\,\frac{R_{\max}-\mu_{\mathrm{m}}}{\sigma_{\mathrm{m}}+\epsilon}. \tag{8}$$

The oracle sequence is excluded from μ_{m} and σ_{m}, so it does not alter the model-rollout advantages. Under the binary reward, A^+ is positive only for groups containing both successful and unsuccessful rollouts: the gate sets it to zero for all-fail groups, and the numerator is zero for all-success groups. Both homogeneous cases also yield zero model-rollout advantages. Unlike fixed-weight SFT mixing, the anchor weight therefore depends on the sampled group's rewards; unlike inserting oracle completions into the comparison group, it leaves the baseline unchanged (Yan et al., 2026; Zhang et al., 2026).

3.5 Training Objective

For a model-generated completion $y_{k,j}$, we use the clipped GRPO objective

$$\ell_{\mathrm{clip}}(y_{k,j}, A_{k,j}) = \sum_t \min\left(\rho_{k,j,t}A_{k,j}, \bar{\rho}_{k,j,t}A_{k,j}\right),$$
$$\bar{\rho}_{k,j,t} = \mathrm{clip}\left(\rho_{k,j,t}, 1-\epsilon_{\mathrm{clip}}, 1+\epsilon_{\mathrm{clip}}\right), \tag{9}$$

where

$$\rho_{k,j,t} = \frac{\pi_\theta(y_{k,j,t} \mid V_k, q, y_{k,j,<t})}{\pi_{\theta_{\mathrm{old}}}(y_{k,j,t} \mid V_k, q, y_{k,j,<t})}. \tag{10}$$

The oracle sequence is not an on-policy sample. We therefore optimize it as an advantage-weighted supervised anchor:

$$\ell_{\mathrm{anchor}}(y^+, A^+) = \mathrm{sg}(A^+)\sum_t \log \pi_\theta\left(y_t^+ \mid V_{k^+}, q, y_{<t}^+\right), \tag{11}$$

Table 1: **Overall results of VISTA across five GUI-grounding benchmarks.** We highlight the best and second-best results within each model size category. * denotes our evaluated results.

Model	SSPro	SSV2	MMBench-L2	OSWorld-G-R	OSWorld-G	Avg.
≈4B						
Qwen3-VL-4B* (Bai et al., 2025)	55.5	88.5	85.3	67.9	58.2	71.1
Step-GUI-4B (Yan et al., 2025)	60.0	93.6	84.0	66.9	60.5	73.0
VISTA-4B	63.4	94.4	86.7	69.4	63.8	75.5
+ *MVP*	71.6	94.5	86.8	69.6	64.0	77.3
≈8B						
UI-TARS-1.5-7B (Qin et al., 2025b)	35.7	91.6	64.3	64.2	52.8	61.7
OpenCUA-7B (Wang et al., 2025c)	50.0	92.3	-	-	55.3	-
GTA1-7B (Yang et al., 2025)	50.1	92.4	-	67.7	60.1	-
UI-Venus-7B (Gu et al., 2025a)	50.8	94.1	79.9	61.7	54.6	68.2
GUI-Owl-7B (Ye et al., 2025)	54.9	92.8	80.5	-	55.9	-
Step-GUI-8B (Yan et al., 2025)	62.6	95.1	85.6	70.0	-	-
Qwen3-VL-8B* (Bai et al., 2025)	52.7	91.7	81.3	64.4	54.8	69.0
Holo2-8B (Company, 2025)	58.9	93.2	84.5	70.1	63.5	74.0
MAI-UI-8B (Zhou et al., 2025a)	65.8	95.2	88.8	68.6	60.1	75.7
VISTA-8B	65.8	95.5	86.8	70.8	62.4	76.3
+ *MVP*	72.0	95.6	87.3	70.9	63.1	77.8
≥30B						
Qwen3-VL-30B-A3B* (Bai et al., 2025)	53.7	94.7	83.7	69.3	66.5	73.6
Holo2-30B-A3B (Company, 2025)	66.1	94.9	86.8	76.1	65.2	77.8
OpenCUA-32B (Wang et al., 2025c)	55.3	93.4	-	70.2	59.6	-
GUI-Owl-32B (Ye et al., 2025)	58.0	93.1	83.0	-	58.0	-
GTA1-32B (Yang et al., 2025)	63.6	95.2	-	72.2	65.2	-
OpenCUA-72B (Wang et al., 2025c)	60.8	92.9	-	-	-	-
UI-Venus-72B (Gu et al., 2025a)	61.9	95.3	86.3	69.5	62.2	75.0
VISTA-30A3B	67.0	95.2	86.8	72.0	67.1	77.6
+ *MVP*	74.1	95.4	87.6	72.5	67.6	79.4

where $\mathrm{sg}(\cdot)$ denotes stop-gradient.

For M anchors per group, we repeat the above construction to obtain $\{(y_m^+, A_m^+)\}_{m=1}^M$, with each anchor loss conditioned on its selected view. All anchors share the same group-level advantage, $A_m^+ = A^+$, and are excluded from the model-only group statistics. The final loss is

$$\mathcal{L}_{\text{VISTA}} = -\frac{1}{G+M}\left[\sum_{k=1}^{K}\sum_{j=1}^{n}\ell_{\text{clip}}(y_{k,j}, A_{k,j}) + \lambda_{\text{a}}\sum_{m=1}^{M}\ell_{\text{anchor}}(y_m^+, A_m^+)\right] + \beta\mathcal{L}_{\text{KL}}, \tag{12}$$

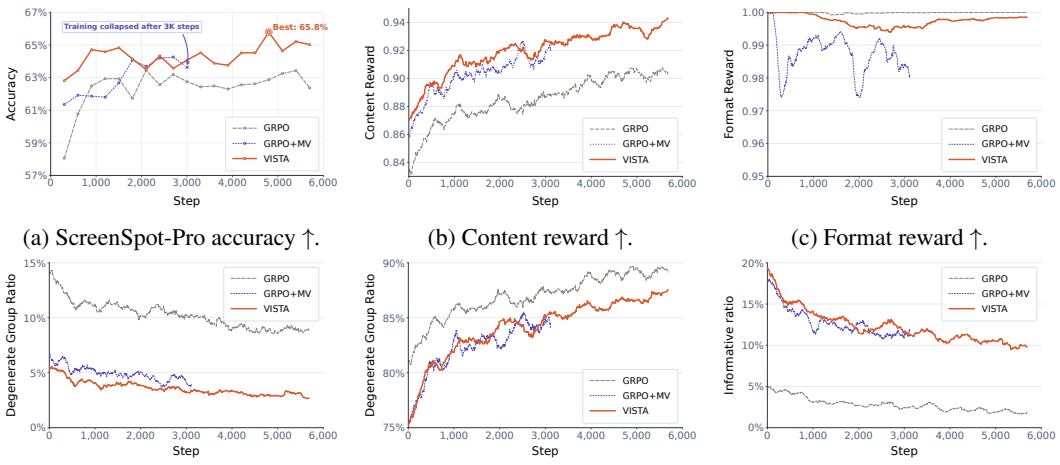
where M is the number of anchor sequences appended to each group, and λ_{a} controls the strength of the anchor loss and is set to 1 unless otherwise specified. In implementation, the M oracle coordinate sequences are appended to the G model completions and optimized through the same token-level training pipeline.

4 Experiments

We evaluate VISTA from three perspectives. First, we test whether view-consistent self-verified training improves GUI grounding across model scales and benchmarks. Second, we examine whether the improvement is tied to a specific Qwen3-VL initialization. Third, we isolate the effects of view-consistent dynamic cropping, self-verified anchoring, and crop-set robustness. Unless otherwise specified, VISTA uses $K{=}G{=}8$ target-preserving views and appends one oracle center-point completion per training block.

4.1 Experimental Setup

Benchmarks and metrics. We report results on five GUI-grounding benchmarks: ScreenSpot-Pro (Li et al., 2025), ScreenSpot-V2 (Wu et al., 2024), MMBench-GUI L2 (Xuehui Wang et al., 2025), OSWorld-G-R, and OSWorld-G (Xie et al., 2025). These benchmarks cover mobile, web,



(a) ScreenSpot-Pro accuracy ↑. (b) Content reward ↑. (c) Format reward ↑.

(d) All-zero degenerate ratio ↓. (e) All-one degenerate ratio ↓. (f) Informative group ratio ↑.

Figure 3: **Training dynamics and reward diagnostics.** Degenerate group ratios: "All-zero" groups contain only zero-reward responses, while "All-one" groups contain only full-reward responses; both are uninformative for policy-gradient updates and lower is better. The informative group ratio, $1 - \text{ratio}_{\text{all-zero}} - \text{ratio}_{\text{all-one}}$, is the share of non-degenerate groups containing both successful and unsuccessful rollouts.

desktop, and high-resolution professional software interfaces. For all datasets, the model predicts a normalized coordinate in the 0–1000 frame, and a prediction is counted as correct when the point falls inside the target element. We use accuracy as the primary metric and report the average over the listed benchmarks when all required numbers are available in the corresponding table. All evaluations are conducted with deterministic decoding at temperature 0.

Models and baselines. Our main experiments instantiate VISTA on Qwen3-VL backbones at the 4B, 8B, and 30B-A3B scales. We compare against the original Qwen3-VL models and recent GUI grounding models within the same parameter-scale groups. All VISTA rows use standard single-view inference unless marked with + *MVP*. MVP (Zhang et al., 2025c) is an orthogonal inference-time multi-view aggregation method; we include it to test whether a model trained with view-consistent rollouts remains compatible with test-time view aggregation. For cross-backbone evaluation, we additionally train Qwen3.5-initialized models and compare VISTA against standard GRPO under the same backbone family.

Training dataset and cost. We train VISTA on roughly 120K GUI-grounding samples curated from open-source datasets, including SeeClick (Cheng et al., 2024), Widget Captioning (Li et al., 2020), ShowUI-web (Lin et al., 2024), UI-RefExp (Bai et al., 2021), OmniAct (Kapoor et al., 2024). Compared with standard GRPO, VISTA incurs a moderate training overhead: across different model sizes, training for the same number of steps increases wall-clock time by approximately 25% under the same training setup.

Implementation details. Unless otherwise specified, each group contains $G{=}8$ model rollouts and $M{=}1$ oracle anchor, with $\lambda_{\text{a}}{=}1$. With probability $p_{\text{crop}}{=}0.8$, we sample one completion from each of $K{=}8$ target-preserving crops; otherwise, all eight completions use the original screenshot ($K{=}1$, $n{=}8$). We train with DeepSpeed ZeRO-3, bfloat16 precision, frozen vision modules, a learning rate of $1{\times}10^{-6}$, KL coefficient $\beta{=}0.04$, and total batch size 128.

4.2 Main Results

Table 1 shows that VISTA consistently improves the Qwen3-VL backbone across scales. At 4B, 8B, and 30B-A3B, the average score increases from 71.1/69.0/73.6 to 75.5/76.3/77.6, respectively. The largest gains appear on ScreenSpot-Pro, where small targets and dense high-resolution interfaces make coordinate errors especially costly: VISTA improves Qwen3-VL by +7.9, +13.1, and +13.3

Table 2: **Cross-backbone generalization with Qwen3.5-initialized models.**

Method	SSPro	SSV2	OS -G	OS-G-R
4B				
Qwen3.5-4B	60.3	90.4	54.4	66.8
GRPO-4B	62.2	**94.2**	59.9	69.2
VISTA-4B	**64.2**	93.8	**61.2**	**69.7**
Δ	**+2.0**	-0.4	**+1.3**	**+0.5**
9B				
Qwen3.5-9B	65.2	91.9	63.1	74.6
GRPO-9B	68.3	95.2	67.5	75.2
VISTA-9B	**69.2**	**95.8**	**68.1**	**75.5**
Δ	**+0.9**	**+0.6**	**+0.6**	**+0.3**
35B-A3B				
Qwen3.5-35B-A3B	68.6	93.8	65.8	72.5
GRPO-35B-A3B	71.7	95.7	70.4	74.3
VISTA-35B-A3B	**72.9**	**95.8**	**71.5**	**75.3**
Δ	**+1.2**	**+0.1**	**+1.1**	**+1.0**

Table 3: **Ablation study on the components of VISTA.** The shaded row marks the full model with dynamic cropping and adaptive supervision. View group denotes view-consistent rollout groups; Anchor denotes self-verified adaptive anchor supervision.

Method	Components		Accuracy ↑	
	View group	Anchor	SSV2	SSPro
Qwen3-VL-8B	✗	✗	91.7	52.7
SFT	✗	✗	93.6	59.8
SFT + aug	✗	✗	94.6	60.5
GRPO	✗	✗	95.2	63.4
GRPO + aug	✗	✗	95.1	64.0
GRPO + crop	✓	✗	95.4	64.3
GRPO + anchor	✗	✓	95.3	64.8
VISTA	✓	✓	**95.5**	**65.8**

points at the three scales. By contrast, ScreenSpot-V2 is already near saturation for strong GUI models, so the gains there are smaller but still positive. Relative to standard GRPO, VISTA improves ScreenSpot-Pro by 1.9, 2.4, and 1.1 points at the three scales, respectively (Appendix Table 12).

VISTA also combines well with inference-time multi-view prediction. Adding MVP further raises the average scores to 77.3, 77.8, and 79.4 at the 4B, 8B, and 30B-A3B scales. The improvement is again most pronounced on ScreenSpot-Pro, where the + *MVP* rows reach 71.6, 72.0, and 74.1. These additional gains show that VISTA remains compatible with inference-time view aggregation.

Figure 3 summarizes the training dynamics and reward diagnostics. Compared with standard GRPO, multi-view rollout reduces all-zero degeneracy and improves content reward, but its format reward is noticeably unstable during training. With self-verified anchoring, VISTA maintains a high and stable format reward while improving content reward and ScreenSpot-Pro accuracy.

4.3 Cross-Backbone Generalization

To test whether VISTA depends on Qwen3-VL initialization, we train Qwen3.5-initialized backbones at 4B, 9B, and 35B-A3B scales and compare them against standard GRPO. Table 2 reports ScreenSpot-Pro gains of 2.0, 0.9, and 1.2 points, respectively, with improvements on both OSWorld-G and OSWorld-G-R at every scale. ScreenSpot-V2 gains are smaller, and the 4B model drops by 0.4 points, indicating that improvements are not uniform across benchmarks.

4.4 Ablation Study

Table 3 isolates the two components of VISTA on the 8B model. Crop augmentation improves SFT from 59.8 to 60.5 on ScreenSpot-Pro. Within RL, GRPO + aug reaches 64.0, compared with 63.4 for

Table 4: **Ablation study on anchor supervision** (Qwen3-VL-8B). Adaptive gating avoids unverified oracle updates while preserving a model-only baseline. Gate denotes self-verified adaptive activation.

Anchor	Gate	SSV2	SSPro
None	–	95.4	64.3
Normalized	✗	93.8	57.8
Const. SFT	✗	94.8	63.9
Normalized	✓	**95.5**	**65.8**

Table 5: **Comparison under different view settings.** Worst denotes worst-view accuracy; VCR is correctness-consistency rate across views; Flip is correctness flip rate; Base is Qwen3-VL-8B.

Model	Accuracy ↑			VCR ↑	Flip ↓
	Orig.	Crop	Worst		
Base	81.6	81.3	71.5	75.6	17.3
GRPO	94.0	93.0	87.6	88.4	8.3
VISTA	**95.6**	**96.3**	**92.4**	**93.6**	**5.8**

standard GRPO and 64.3 for cross-view grouping alone. GRPO + aug uses the same target-preserving crop augmentation as cross-view grouping, but all rollouts within a group share one sampled crop; cross-view grouping instead samples multiple crops within each augmented group. Self-verified anchoring alone reaches 64.8, while combining both components gives 65.8 on ScreenSpot-Pro and 95.5 on ScreenSpot-V2. The full method exceeds GRPO + aug by 1.8 points on ScreenSpot-Pro, whereas grouping alone provides a smaller gain of 0.3 points.

Supervision strategy. Table 4 compares different anchor-supervision strategies under the GRPO + multi-view rollout setting. Simply adding a normalized oracle anchor without gating severely hurts performance, dropping ScreenSpot-Pro from 64.3 to 57.8. For all-zero groups, $\mu_{\mathrm{m}} = \sigma_{\mathrm{m}} = 0$, so an ungated reward-1 anchor receives a weight of $1/\epsilon$ and can dominate the update. Constant-weight SFT avoids this large weight but underperforms the no-anchor baseline, reaching 63.9 versus 64.3 on ScreenSpot-Pro. Our gated anchor receives positive weight only in mixed-reward groups; both all-fail and all-success groups receive zero anchor weight. This yields the best results, 95.5 on ScreenSpot-V2 and 65.8 on ScreenSpot-Pro.

Additional ablations support the single-anchor default: increasing M from one to two or four reduces ScreenSpot-Pro accuracy from 65.8 to 65.0 and 64.0, respectively (Appendix Table 7). Thus, increasing the number of oracle sequences does not improve performance under the tested settings.

4.5 Crop Perturbation Diagnostic

We measure sensitivity to crop perturbations on training examples. We sample 1250 training examples and, for each, evaluate the original view with eight randomly cropped target-preserving views, using the same crop procedure as training. We report original and crop-view accuracy, worst-view accuracy, view consistency rate (VCR), and correctness flip rate. VCR and flip rate compare correctness labels across views, rather than predicted coordinates (Appendix A.2). Table 5 reports higher accuracy and more consistent correctness labels for VISTA. Compared with standard GRPO, VISTA raises crop accuracy from 93.0% to 96.25%, worst-view accuracy from 87.6% to 92.4%, and VCR from 88.4% to 93.4%. It also reduces the correctness flip rate from 8.3% to 5.8%. This diagnostic uses the training crop distribution and does not establish robustness to unseen transformations.

5 Conclusion

We presented VISTA, a view-consistent self-verified training framework that uses target-preserving cropped views, exact coordinate remapping, and a self-verified oracle anchor to better align RL with GUI grounding. Across benchmarks, scales, and backbones, VISTA improves accuracy and crop robustness, suggesting that view-consistent group construction is an effective training signal for GUI grounding.

AI USE STATEMENT

Generative AI tools were used to assist with code implementation, LaTeX formatting, template migration, and drafting the ethics and reproducibility statements. The authors are responsible for reviewing and verifying all AI-assisted code and edits before submission. The authors take responsibility for the final content of this work, including any text, claims, or artifacts produced with the aid of generative AI.

REPRODUCIBILITY STATEMENT

Section 3 specifies the training objective, view-consistent group rollout, and self-verified cross-view anchoring. Section 4.1 describes the training data sources, backbones, evaluation benchmarks, metrics, and decoding settings. Table 6 lists training hyperparameters, including the data seed, and Appendix A.2 details the target-preserving crop sampling and coordinate transformations. These descriptions provide the methodological and implementation details needed to understand and reproduce the reported experimental procedure.

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A Appendix

A.1 Training Details

The key optimization and training hyperparameters for the VISTA experiments are summarized in Table 6.

Table 6: Hyperparameter settings used in the VISTA training experiments.

Hyperparameter	**Value**
deepspeed	ZeRO-3
freeze_vision_modules	true
max_prompt_length	4096
num_generations	8
per_device_train_batch_size	8
gradient_accumulation_steps	4
bf16	true
torch_dtype	bfloat16
data_seed	42
gradient_checkpointing	true
attn_implementation	flash_attention_2
num_train_epochs	100
learning_rate	1e-6
β	0.04
logging_steps	1

A.2 Implementation Details of View-Consistent Group Rollout

Our implementation follows the target-preserving crop construction described in the main method. For each training example, we first decide whether to use view augmentation by a deterministic index-seeded Bernoulli sampler: 80% of examples use dynamic crops, while 20% remain pass-through examples with repeated original views. This pass-through branch keeps standard full-screen layouts in the training distribution.

For augmented examples, let the original image size be $W \times H$, and let the normalized ground-truth box be $B = (x_1, y_1, x_2, y_2) \in [0, 1]^4$; here we divide the main-text coordinates by 1000 for the pixel conversion below. We convert it to pixel coordinates as

$$B^{\text{px}} = (x_1 W, y_1 H, x_2 W, y_2 H).$$

For each cropped view k, the initial crop size is set to $(w_k, h_k) = (0.9W,\ 0.9H)$. If the crop width or height is smaller than the target box itself, that dimension is enlarged to the box size and clipped by the image boundary. This corner-case handling guarantees that the target UI element is never truncated, even for large elements or narrow screenshots. Each crop window is then sampled from the feasible range of top-left locations that fully contain B^{px}, ensuring target preservation across all augmented views.

We then compute the feasible integer range for the crop's top-left corner so that the full target box is inside the crop:

$$\begin{aligned} l &\in [\max(0, x_2 W - w), \min(W - w, x_1 W)], \\ t &\in [\max(0, y_2 H - h), \min(H - h, y_1 H)]. \end{aligned} \tag{13}$$

The implementation samples eight independent crop windows from these feasible ranges, matching `num_generations=8`. For each crop, the target box is remapped exactly into the crop coordinate frame,

$$\begin{aligned} B' = (&\frac{x_1 W - l}{w}, \frac{y_1 H - t}{h}, \\ &\frac{x_2 W - l}{w}, \frac{y_2 H - t}{h}), \end{aligned} \tag{14}$$

clipped to $[0, 1]$, and finally converted to the model's 0–1000 coordinate system. Each cropped image is resized again with `smart_resize` before being passed to the VLM, but the supervision coordinates

are computed from the pre-resize crop geometry, so the rollout group remains view-consistent under the crop-induced coordinate transform.

Metric definitions for Table 5. For each instance, let c_0 denote the correctness on the original view and c_m denote the correctness on crop view m, $m = 1, \ldots, 8$. We define the correctness flip rate as

$$\frac{1}{8} \sum_{m=1}^{8} \mathbb{I}[c_m \neq c_0],$$

averaged over instances.

VCR is the fraction of instances for which all nine views have the same correctness label:

$$\mathbb{I}[c_0 = c_1 = \cdots = c_8].$$

These metrics compare correctness labels, not the coordinates of the predicted clicks.

A.3 Additional Ablation and Analysis

Table 7: **Ablation study on the number of oracle anchors.** The shaded row indicates the default single-anchor setting.

Anchors	SSV2	SSPro
1	95.5	65.8
2	95.3	65.0
4	95.2	64.0

Additional Ablation: Number of Oracle Anchors Table 7 compares one, two, and four oracle anchors per group. Increasing the number of supervised completions from 1 to 2 or 4 reduces ScreenSpot-Pro accuracy from 65.8 to 65.0 and 64.0. All anchors remain gated and share the same group-level advantage. Increasing M changes the relative contribution of anchor supervision and, through the $G + M$ denominator, the scaling of the model-rollout term. The results favor a single anchor under this objective, but do not isolate which change in loss weighting causes the decline.

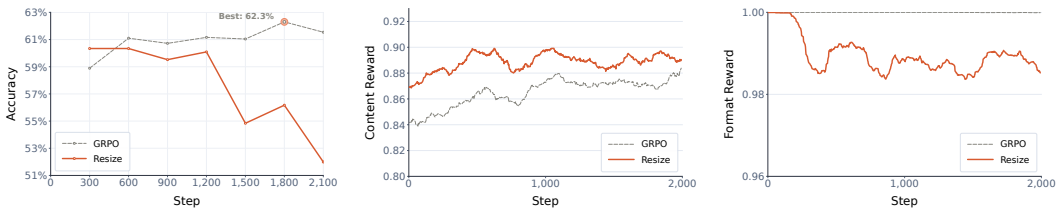
Table 8: **Ablation study on the oracle-anchor point choice** (Qwen3-VL-8B).

Oracle Anchor Point	SSV2	SSPro
Box center	95.5	65.8
Random point in GT box	95.2	64.8

Additional Ablation: Oracle-anchor point choice. Table 8 studies whether the oracle anchor is sensitive to using the ground-truth box center. We compare the default center-point anchor against an anchor sampled uniformly from inside the ground-truth bounding box, using the same Qwen3-VL-8B setting. The random-point variant reaches 95.2 on ScreenSpot-V2 and 64.8 on ScreenSpot-Pro, close to but below the default center-point anchor at 95.5 and 65.8. Thus, the method remains effective with randomly sampled valid target points, although the deterministic center yields higher accuracy in this comparison. We use the box center as the default to avoid additional randomness in the anchor coordinates.

Table 9: **Ablation study on the number of target-preserving views.** The shaded row indicates the default setting used by VISTA.

Views	SSV2	SSPro
K=1	95.3	64.8
K=2	95.2	64.8
K=4	95.5	64.4
K=8	95.5	65.8



(a) ScreenSpot-Pro accuracy ↑. (b) Content reward ↑. (c) Format reward ↑.

Figure 4: **Resize strategy training dynamics and reward diagnostics.**

Additional Ablation: Number of views. Table 9 studies the number of target-preserving views. Accuracy does not increase monotonically with the number of views: ScreenSpot-Pro scores are 64.8, 64.8, 64.4, and 65.8 for $K{=}1, 2, 4, 8$, respectively. We use $K{=}8$ in the main experiments because it obtains the best ScreenSpot-Pro accuracy, 65.8, while matching the GRPO group size used in our method.

Table 10: **Ablation study on crop strategies.** Dynamic crop provides the strongest ScreenSpot-Pro accuracy.

Crop Strategy	SSV2	SSPro
No crop	95.3	64.8
Cross-offset crop	95.7	65.0
Dynamic crop	95.5	65.8

Additional Ablation: Crop strategy. Table 10 compares different crop constructions. Cross-offset cropping gives the highest ScreenSpot-V2 number, but dynamic cropping performs best on ScreenSpot-Pro. These results favor dynamic cropping for ScreenSpot-Pro, while showing that no crop strategy is uniformly best across both benchmarks.

Table 11: **Ablation study on p_{crop}.**

p_{crop}	SSV2	SSPro
1.0	95.1	64.6
0.8	95.5	65.8
0.6	95.6	65.2

Additional Ablation: p_{crop}. Table 11 studies the probability of applying target-preserving crop augmentation during training. As described in Section 3, p_{crop} controls the mixture between view-consistent cropped groups and pass-through full-screen groups. A larger value exposes the policy to more crop-induced coordinate transformations, while a smaller value retains more original screenshots and reduces train–test mismatch. Using crops for every example yields 64.6 on ScreenSpot-Pro, compared with 65.8 at $p_{\text{crop}}{=}0.8$, supporting the inclusion of full-screen examples under the tested setup. Reducing the probability to $p_{\text{crop}}{=}0.6$ slightly improves ScreenSpot-V2 to 95.6 but lowers ScreenSpot-Pro to 65.2, illustrating a benchmark-dependent trade-off. We therefore use $p_{\text{crop}}{=}0.8$ in the main experiments, which achieves the best ScreenSpot-Pro accuracy, 65.8, while maintaining strong ScreenSpot-V2 accuracy, 95.5.

Additional Ablation: Image processing strategy. We test whether multiple image inputs alone provide the same benefit as target-preserving crops. Starting from Qwen3-VL-4B, we compare standard GRPO with groups of differently resized versions of the same full screenshot. Resizing changes visual scale and tokenization while preserving normalized target coordinates. Figure 4 reports training rewards and ScreenSpot-Pro accuracy, evaluated every 300 steps from step 300.

Although multi-image resize initially slightly outperforms GRPO, its accuracy drops from 60.34 at step 300 to 51.99 at step 2100. GRPO remains relatively stable and ends at 61.54, a final gap of 9.55 points.

Table 12: Performance comparison on the **ScreenSpot-Pro.** * denotes our evaluated results.

Model	CAD		Dev.		Creative		Scientific		Office		OS		Avg.
	Text	Icon	Text	Icon	Text	Icon	Text	Icon	Text	Icon	Text	Icon	
≈4B													
Qwen3-VL-4B* (Bai et al., 2025)	53.3	18.8	78.6	31.7	70.7	22.4	75.7	30.0	83.1	39.6	76.6	33.7	55.5
GRPO-4B	65.5	25.0	79.9	40.0	71.2	28.7	83.3	40.0	90.4	47.2	74.8	39.3	61.5
VISTA-4B	64.0	28.1	81.1	45.2	72.7	33.6	81.9	40.0	89.8	54.7	76.6	40.5	63.4
+ *MVP*	79.2	51.6	87.2	53.4	74.2	48.3	85.4	50.0	92.1	73.6	78.5	61.8	71.6
≈8B													
UI-TARS-7B (Qin et al., 2025a)	20.8	9.4	58.4	12.4	50.0	9.1	63.9	31.8	63.3	20.8	30.8	16.9	35.7
Phi-Ground (Zhang et al., 2025b)	26.9	17.2	70.8	16.7	56.6	13.3	58.0	29.1	76.4	44.0	55.1	25.8	43.2
GUI-Actor-7B (Wu et al., 2025)	47.7	9.4	59.1	15.9	59.6	16.1	70.1	25.5	69.5	41.5	55.1	19.1	44.6
SE-GUI-7B (Yuan et al., 2025)	51.3	14.1	68.2	19.3	57.6	9.1	75.0	28.2	78.5	43.4	49.5	25.8	47.2
GUI-G^2-7B (Tang et al., 2025a)	55.8	12.5	68.8	17.2	57.1	15.4	77.1	24.5	74.0	32.7	57.9	21.3	47.5
OpenCUA-7B (Wang et al., 2025c)	-	-	-	-	-	-	-	-	-	-	-	-	50.0
GTA1-7B (Yang et al., 2025)	53.3	17.2	66.9	20.7	62.6	18.9	76.4	31.8	82.5	50.9	48.6	25.9	50.1
UI-Venus-7B (Gu et al., 2025a)	60.4	21.9	74.7	24.1	63.1	14.7	76.4	31.8	75.7	41.5	49.5	22.5	50.8
InfiGUI-G1-7B (Liu et al., 2025)	57.4	23.4	74.7	24.1	64.6	18.2	80.6	31.8	75.7	39.6	57.0	29.2	51.9
GUI-Owl-7B (Ye et al., 2025)	64.5	21.9	76.6	31.0	59.6	27.3	79.1	37.3	77.4	39.6	59.8	33.7	54.9
MAI-UI-8B (Zhou et al., 2025a)	72.6	35.9	83.8	52.4	76.3	33.6	79.9	37.3	88.7	60.4	76.6	49.4	65.8
Qwen3-VL-8B* (Bai et al., 2025)	56.9	10.9	75.3	22.8	68.2	16.1	78.5	32.7	80.8	39.6	71.0	20.2	52.7
GRPO-8B	73.6	31.2	82.5	39.3	77.8	28.0	81.9	40.0	88.7	49.1	73.8	40.4	63.4
VISTA-8B	74.6	34.4	85.3	45.9	73.7	29.4	81.9	40.9	91.5	58.5	76.6	42.7	65.8
+ *MVP*	81.7	45.3	89.1	58.2	76.3	42.7	86.1	56.9	92.1	71.7	80.4	53.9	72.0
≥30B													
Qwen3-VL-32B* (Bai et al., 2025)	60.4	28.1	69.5	22.1	75.8	25.2	84.7	25.5	85.9	43.4	62.6	15.7	54.9
OpenCUA-32B (Wang et al., 2025c)	-	-	-	-	-	-	-	-	-	-	-	-	55.3
GUI-Owl-32B (Ye et al., 2025)	62.4	28.1	84.4	39.3	65.2	18.2	82.6	39.1	81.4	39.6	70.1	36.0	58.0
GTA1-32B (Yang et al., 2025)	43.7	23.4	82.5	28.3	69.2	14.7	79.9	31.8	80.8	43.4	70.1	32.6	63.6
MAI-UI-32B (Zhou et al., 2025a)	70.1	45.3	86.4	40.7	82.8	37.8	91.7	46.4	90.4	71.7	78.5	34.8	67.9
UGround-v1-72B (Gou et al., 2025)	16.8	4.7	55.8	4.8	54.0	10.5	70.8	22.7	61.0	18.9	40.2	7.9	34.5
UI-Tars-72B (Qin et al., 2025a)	18.8	12.5	63.0	17.2	57.0	15.4	64.6	20.9	63.3	26.4	42.1	15.7	38.1
UI-Venus-72B (Gu et al., 2025b)	66.5	29.7	84.4	33.1	73.2	30.8	84.7	42.7	83.1	60.4	75.7	36.0	61.9
Qwen3-VL-30A3B* (Bai et al., 2025)	51.8	15.6	76.0	24.8	69.2	20.3	76.4	27.3	80.8	37.7	75.7	38.2	53.7
GRPO-30A3B	69.5	29.7	84.4	51.7	74.7	33.6	81.9	40.0	89.3	52.8	83.2	53.9	65.9
VISTA-30A3B	71.1	32.8	85.9	52.1	76.8	35.7	83.3	38.2	87.0	56.6	78.5	50.6	67.0
+ *MVP*	82.7	45.3	89.7	58.2	79.8	51.8	86.8	49.1	92.1	71.7	83.2	60.7	74.1

One possible explanation is that full-image resizing provides multiple visual inputs with the same normalized target coordinates. Target-preserving cropping instead changes the target's relative position, requiring the model to adapt its coordinate output to each view. This distinction may contribute to the different training behavior, but the experiment does not isolate coordinate variation from changes in visual context and image tokenization.

Detailed ScreenSpot-Pro results. Table 12 provides the category-level ScreenSpot-Pro breakdown behind the aggregate SSPro numbers in Table 1. Across the 4B, 8B, and 30A3B settings, VISTA improves the corresponding GRPO baseline by 1.9, 2.4, and 1.1 percentage points, respectively. Adding MVP further improves ScreenSpot-Pro accuracy at each scale.