



See2Think: Do Multimodal Models Really Use Intermediate Visual States?

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Abstract

Multimodal large language models increasingly use sketches, annotations, tools, and intermediate images during reasoning, but it remains unclear whether they truly rely on these visual states. Existing benchmarks are limited both by task collections with narrow coverage or partially text-solvable samples and by evaluations that emphasize final answers without diagnosing how intermediate visual states are generated, rendered, and used. We introduce **See2Think**, a unified evaluation framework comprising **See2ThinkBench** and **Visual Action-of-Thought (VAoT)**. See2ThinkBench contains **1,200 open-ended, visually dependent problems** across 12 task categories spanning 2D structured, 3D scene, and real-world reasoning. VAoT records textual thoughts, visual actions, rendered states, and subsequent reasoning under four controlled inference settings. Evaluating representative proprietary and open-source multimodal models, we find that visual reasoning is strongly model- and environment-dependent, with no single setting consistently dominating across tasks. Process analysis further shows that models usually select relevant visual operations, while faithful rendering remains the clearest bottleneck and high feedback uptake does not necessarily translate into accuracy gains. Under task-relevant corrupted feedback, models exhibit behavioral dependence on visual states, with accuracy dropping by **over 10 percentage points** in 3D scenes. See2Think disentangles visual-state utility from behavioral dependence and provides a unified framework for evaluating whether multimodal models genuinely use intermediate visual states.

Website: <https://sgysy.github.io/seetothink/>

Repository: <https://github.com/CSU-JPG/See2Think>

1 Introduction

Chain-of-Thought (CoT) reasoning improves language-model reasoning by externalizing intermediate textual steps [22]. Many multimodal problems, however, are not naturally solved through text alone. Humans draw auxiliary lines, mark relevant regions, compare structures, and sketch intermediate states to externalize spatial and perceptual relations. Recent multimodal systems similarly generate visual scratchpads, invoke visual tools, highlight or crop image regions, and construct intermediate images during reasoning [7, 19–21, 28, 30].

Building on this idea, recent work has rapidly expanded both the methods and evaluations for thinking

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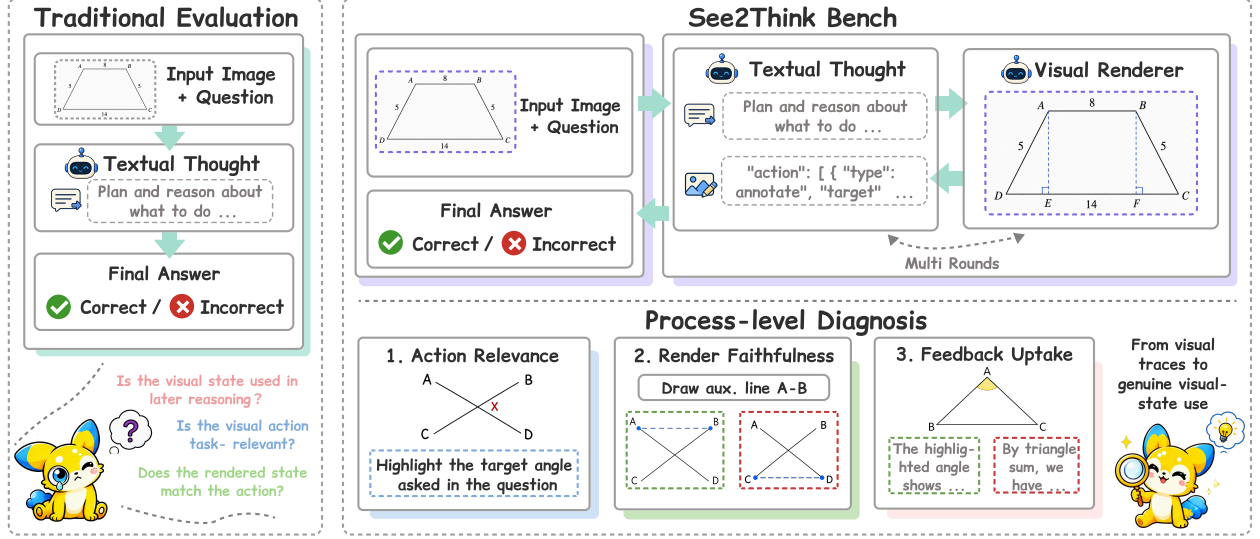


Figure 1 See2Think versus prior visual-reasoning benchmarks. Prior benchmarks mainly evaluate final answers or visual-trace quality. See2Think diagnoses action relevance, render faithfulness, and feedback uptake. Controlled interventions test whether models rely on the returned visual state.

with images. Models now crop, annotate, sketch, manipulate, or generate intermediate visual states through external tools, interactive image generation, continuous visual actions, and repeated visual access [6, 7, 11, 12, 19–21, 25, 29, 30]. Benchmarks such as MIRA, ViC-Bench, TWI-PRMBench, and TwiFF-Bench evaluate oracle visual clues, free-form interleaved states, process quality, or dynamic future-frame reasoning [14, 23, 31, 32]. Recent diagnostic studies further question whether tool calls or generated thinking images are actually answer-critical [3, 24].

Two limitations nevertheless remain. At the data level, existing task collections may have limited visual diversity and are not always screened for text-only shortcuts. At the evaluation level, standard multimodal benchmarks emphasize final answers [17, 26], while multimodal CoT evaluations mainly assess textual rationales [8]. Visual-thinking benchmarks introduce sketches, tools, or intermediate images, but are commonly evaluated through end-task performance, oracle-provided visual clues, or aggregate process scores without matched interventions. Consequently, existing evaluations do not jointly determine whether a self-generated visual action is task-relevant, whether the returned state faithfully realizes that action, and whether subsequent reasoning behaviorally depends on the returned visual evidence.

We introduce **See2Think**, a unified framework for evaluating whether multimodal models genuinely think with intermediate visual states. See2Think contains two complementary components. **See2ThinkBench** provides **1.2K visually dependent reasoning problems** across 12 task categories and three visual environments: 2D structured reasoning, 3D scene reasoning, and real-world visual reasoning. Caption-only solvability filtering reduces text-dominant shortcuts. Most tasks use free-form answer generation, while a small subset retains structured candidate sets inherited from source benchmarks when those candidates form part of the reasoning problem. **Visual Action-of-Thought (VAoT)** provides the inference-time protocol: it records alternating textual thoughts, visual actions, rendered states, and subsequent reasoning. Controlled variants compare CoT, action planning without rendering, standard closed-loop VAoT, and task-relevant corrupted feedback designed to probe behavioral dependence. Together, these components support both outcome-level evaluation and diagnosis of action selection, visual execution, and downstream state use.

Our contributions are:

1. We formulate genuine visual-state use as a **controlled diagnostic problem** and introduce **See2Think**,

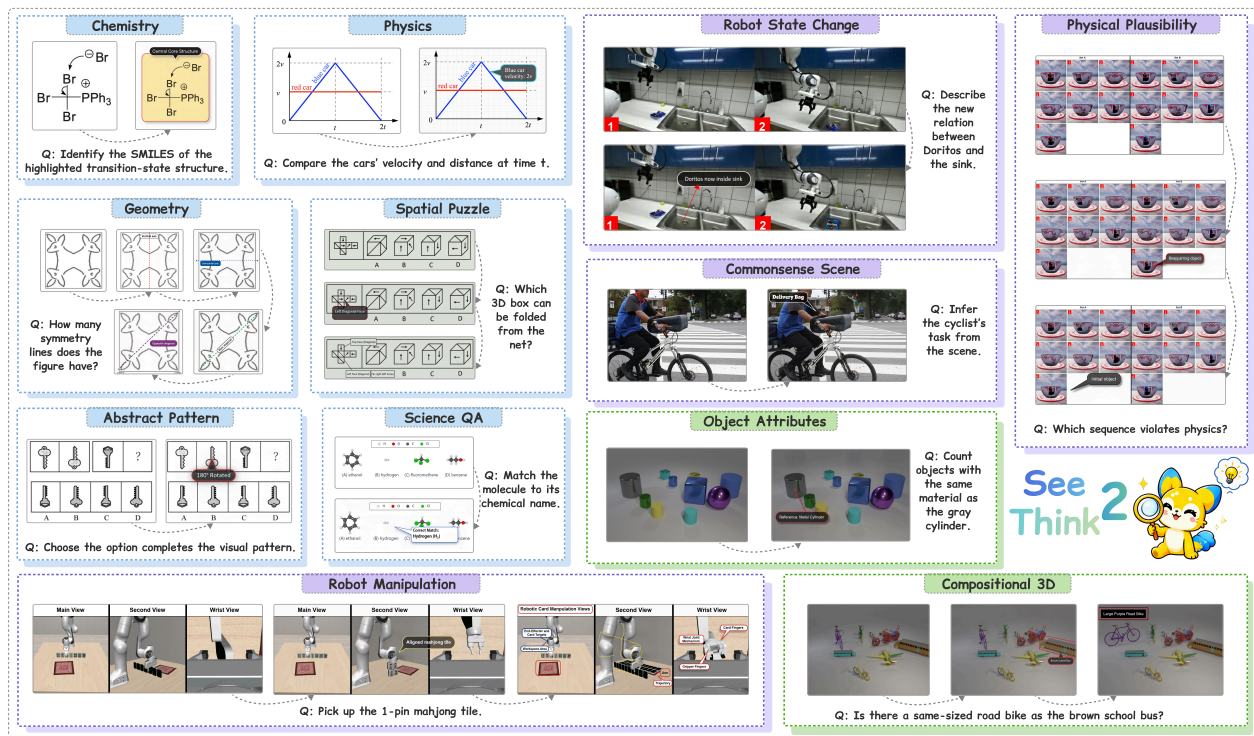


Figure 2 Overview of See2ThinkBench. Representative examples from 12 task categories spanning three visual reasoning levels: 2D structured reasoning, 3D scene reasoning, and real-world visual reasoning.

which distinguishes whether an intermediate visual state is useful from whether model behavior actually depends on it.

2. We construct **See2ThinkBench**, a benchmark of 1.2K visually dependent reasoning problems across 12 task categories and three visual environments. Caption-only solvability filtering reduces text-dominant shortcuts, while answer-format normalization supports consistent evaluation across free-form and structured outputs.
3. We introduce **VAoT**, an observable and intervenable protocol for recording visual actions, rendered states, and their downstream use. Experiments across four representative proprietary and open-source models reveal no universally optimal visual-reasoning strategy, identify a persistent bottleneck after action selection, and expose when rendered feedback helps, harms, or merely decorates the reasoning process.

2 See2ThinkBench

As the data component of See2Think, See2ThinkBench supports controlled outcome- and process-level diagnosis of intermediate visual states in multimodal reasoning. Its construction follows three principles: each problem should require visual evidence, naturally support meaningful visual operations, and permit matched outcome- and process-level evaluation.

2.1 Task Design and Data Sources

See2ThinkBench contains **1.2K visually dependent reasoning samples** from **12 task categories**, with 100 samples in each category. As shown in Figure 2, these categories are organized into three visual reasoning levels: *2D structured reasoning*, *3D scene reasoning*, and *real-world visual reasoning*.

2D structured reasoning. This level comprises six task categories: *Geometry*, *Spatial Puzzle*, *Physics*, *Chemistry*,

Table 1 Comparison with representative benchmarks and evaluation frameworks for visual intermediate reasoning. TWI-PRMBench denotes ThinkWithImages-PRMBench. # Tasks denotes the number of reported task categories or subcategories. Feedback Intervention indicates controlled modification of intermediate visual feedback. Action-Render-Use Diagnosis indicates explicit evaluation of action selection, visual execution, and downstream visual-state use.

Benchmark	# Samples	# Tasks	Generated IVS	Closed-loop	Process Eval.	Feedback Interv.	Action-Render-Use Diagnosis
MIRA [31]	546	20	✗	✗	✗	✗	✗
ViC-Bench [23]	2,751	4	✓	✓	✓	✗	✗
TWI-PRMBench [32]	1,206	16	✓	✗	✓	✗	✗
Twiff-Bench [14]	1,078	3	✓	✓	✓	✓	✗
See2Think (Ours)	1,200	12	✓	✓	✓	✓	✓

Science QA, and *Abstract Pattern*. These problems expose explicit structures such as geometric relations, symbolic diagrams, temporal curves, molecular configurations, and visual transformations. Useful visual operations include drawing auxiliary lines, marking intersections, tracing relations, and annotating symbolic evidence.

3D scene reasoning. This level comprises *Object Attributes* and *Compositional 3D*. The model must identify target objects and reason about attributes, relative positions, counting, comparison, and multi-hop spatial relations. Useful operations include marking objects, isolating regions, tracking relation chains, and filtering distractors.

Real-world visual reasoning. This level comprises *Robot Manipulation*, *Robot State Change*, *Visual Commonsense*, and *Intuitive Physics*. These tasks require semantic grounding, object-state tracking, action understanding, physical plausibility, affordances, and scene-level commonsense. Useful visual operations are less focused on exact geometric construction and more on isolating perceptual evidence and tracking changes across observations.

The source datasets used to instantiate these categories are documented in Appendix A.1; the main paper reports results by semantic task category rather than by source-dataset name.

Table 1 compares See2Think with representative benchmarks for visual intermediate reasoning. MIRA evaluates the benefit of annotated intermediate visualizations, ViC-Bench supports free-form visual-interleaved trajectories, TWI-PRMBench focuses on process reward modeling, and Twiff-Bench extends visual reasoning to dynamically generated future states. See2Think differs by combining explicit text-shortcut filtering with self-generated closed-loop visual states, stage-wise diagnosis of action, rendering, and feedback use, and task-relevant corrupted-feedback interventions.

2.2 Data Construction

Figure 3 summarizes the construction pipeline. Starting from candidate samples collected from existing visual reasoning datasets, we filter out text-dominant cases, normalize the remaining tasks into a unified answer-generation format, and apply automatic and manual quality control for visual dependency, answer uniqueness, and image-question consistency.

Visual dependency filtering. A central concern in multimodal benchmark construction is *text-dominant bias*: some samples can be answered from the question, language priors, or a sufficiently detailed textual description without inspecting the original image. Such samples are unsuitable for diagnosing intermediate visual-state use. For each candidate, we use a strong multimodal model to generate a detailed caption conditioned on both the image and the question. The captioner is instructed to describe only visually observable evidence and not to answer the question or introduce unsupported inference. We then provide a reasoning model with the question and caption while withholding the original image, and query it five times. Samples answered

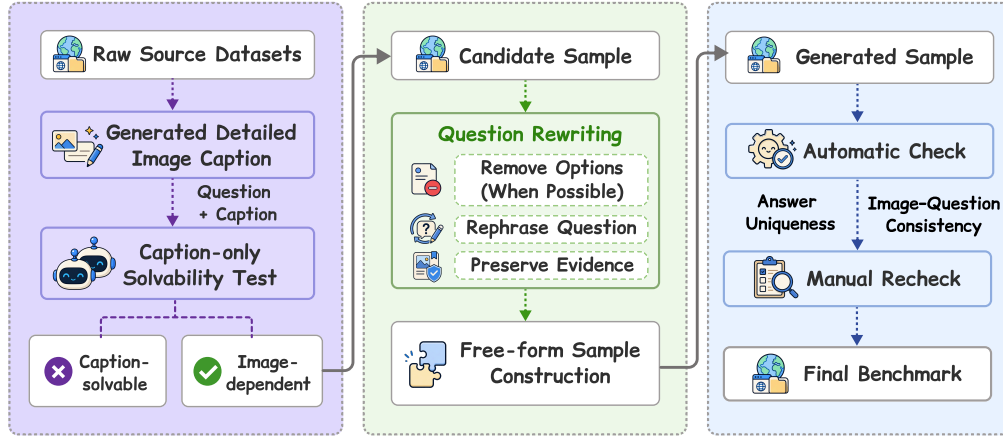


Figure 3 Construction pipeline. Candidate samples are filtered through caption-only answering, converted into a unified answer-generation format, and subjected to automatic checks and manual verification for visual dependency and answer quality.

correctly in at least three trials are considered caption-solvable and removed; the remaining samples are retained as more visually dependent candidates. Prompting and model details are provided in the appendix.

Answer-format conversion. Many source benchmarks contain multiple-choice or template-based questions, which may introduce guessing shortcuts, answer priors, or option-elimination behavior. Whenever possible, we remove textual answer-option lists and rewrite the question as a free-form query while preserving the evidence required to determine a unique answer. A small subset (127 of 1,200 samples) retains structured candidate sets inherited from source tasks because the candidates themselves form part of the reasoning problem; in some cases they appear in the question text, and in others as panels embedded in the original image. These instances are evaluated as structured-answer tasks, while the remaining 1,073 use free-form answers. For natural and embodied scenes, we additionally verify that each question remains grounded in visually observable evidence.

Quality control. The converted problems should require non-trivial reasoning beyond direct visual lookup, admit a unique and reproducible answer, and remain consistent with the associated image. We use a language model to generate candidate rewrites, followed by automatic checks for answer uniqueness and image-question consistency. Each retained sample is then manually rechecked for visual dependency, ambiguity, and compatibility with visual-action reasoning. Samples with underspecified answers, ambiguous visual references, or insufficient visual grounding are revised or removed.

2.3 Evaluation Targets

See2ThinkBench supports two complementary evaluation targets: final-answer correctness and process-level quality. The concrete inference conditions and intervention comparisons are introduced in Section 4; here, we define the evaluation targets supported by the benchmark.

Final-answer correctness. Each sample provides a reference answer for outcome-level evaluation. For structured-answer formats, we use exact matching after standard normalization. For free-form predictions, we evaluate semantic equivalence between the model prediction and the reference answer. This target supports conventional accuracy-based comparison across models and inference conditions.

Process-level quality. For complete VAoT trajectories, we additionally evaluate the quality of the intermediate visual reasoning process. Because a trajectory may contain multiple visual-action calls, we first identify the key visual step or steps most relevant to the final reasoning process. These steps are then evaluated along three dimensions: *action relevance*, which measures whether the requested visual operation targets task-relevant evidence; *render faithfulness*, which measures whether the rendered state correctly realizes the

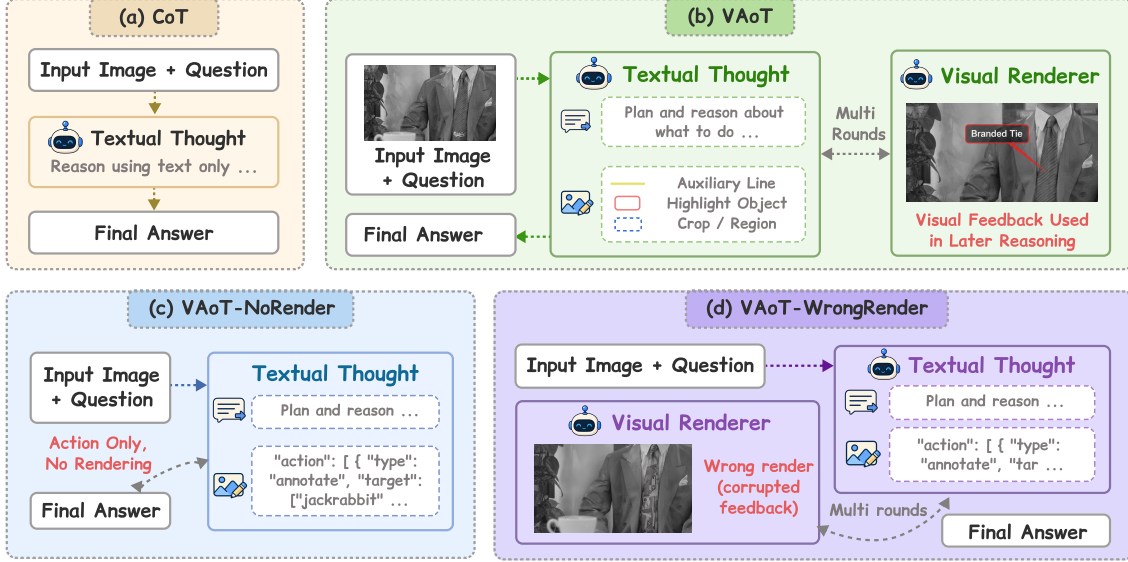


Figure 4 Visual Action-of-Thought. VAoT interleaves textual thoughts, visual actions, and rendered visual states. The model proposes a structured action, the renderer applies a constrained edit to the current image, and the resulting state is returned for subsequent reasoning.

requested operation; and *feedback uptake*, which measures whether subsequent reasoning uses information actually present in the rendered visual state. For diagnostic analysis, incorrect trajectories can additionally be assigned a primary failure source. Detailed scoring protocols are provided in Appendix C, and human validation is reported in Section 4.5.

3 Visual Action-of-Thought

As the protocol component of See2Think, Visual Action-of-Thought (VAoT) records intermediate visual reasoning as an interleaved sequence of textual thoughts, image-grounded actions, and rendered visual states. Because each action can be performed and inspected externally, the trajectory supports controlled intervention and process-level diagnosis. Figure 4 illustrates this closed-loop interaction and its controlled inference settings.

Given an input image I and question q , the model produces a textual thought T_t and a structured visual action A_t on the current visual state. The action specifies an operation, normalized target coordinates, and optional semantic content or style. An external renderer executes it and returns the updated state R_t . The interaction repeats until a final answer is produced:

$$\mathcal{T} = \{T_t, A_t, R_t\}_{t=1}^N. \quad (1)$$

Defining the accumulated history as $\mathcal{H}_t = \{T_i, A_i, R_i\}_{i=1}^t$, the next textual step is

$$T_{t+1} \sim M(I, q, \mathcal{H}_t). \quad (2)$$

The action space includes highlighting objects, drawing auxiliary lines, cropping or zooming into relevant regions, and annotating visual relations. Each action must target visible image content or a visually grounded construction, making the operation executable and externally inspectable.

Renderer principle. The renderer is an external visual workspace that is constrained rather than a task-solving agent. Given the current visual state and a structured action, it executes the requested edit while preserving

Table 2 Overall accuracy on See2ThinkBench. All settings are evaluated on all 1,200 samples, with 100 samples from each task category. The best result among CoT, VAoT-NoRender, and VAoT is highlighted in bold; ties are highlighted jointly. VAoT-WrongRender is excluded from best-score highlighting. Abbreviations: S-Puz. = Spatial Puzzle, AbsPat = Abstract Pattern, ObjAttr = Object Attributes, Comp3D = Compositional 3D, R-Man. = Robot Manipulation, R-State = Robot State Change, V-Comm. = Visual Commonsense, and IntPhys = Intuitive Physics.

Setting	2D Structured Reasoning						3D Scene Reasoning		Real-world Visual Reasoning				Overall
	Geo.	S-Puz.	Phys.	Chem.	SciQA	AbsPat	ObjAttr	Comp3D	R-Man.	R-State	V-Comm.	IntPhys	
GPT-5.5													
CoT	81.0	69.0	48.0	26.0	68.0	40.0	59.0	46.0	1.0	39.0	56.0	69.0	50.2
VAoT-NoRender	60.0	53.0	48.0	23.0	69.0	47.0	72.0	42.0	3.0	34.0	55.0	70.0	48.0
VAoT	46.0	41.0	46.0	28.0	72.0	39.0	68.0	37.0	1.0	38.0	61.0	58.0	44.6
VAoT-WrongRender	55.0	45.0	47.0	20.0	60.0	36.0	60.0	35.0	1.0	36.0	50.0	62.0	42.3
GPT-o3													
CoT	35.0	32.0	42.0	30.0	67.0	37.0	72.0	55.0	1.0	30.0	58.0	63.0	43.5
VAoT-NoRender	24.0	31.0	43.0	30.0	70.0	21.0	74.0	54.0	0.0	29.0	53.0	61.0	40.8
VAoT	24.0	31.0	41.0	19.0	68.0	37.0	76.0	59.0	0.0	32.0	63.0	75.0	43.8
VAoT-WrongRender	27.0	29.0	39.0	19.0	72.0	35.0	61.0	35.0	2.0	31.0	59.0	63.0	39.3
Gemini 3.5 Flash													
CoT	84.0	74.0	68.0	15.0	75.0	55.0	94.0	61.0	1.0	42.0	35.0	80.0	57.0
VAoT-NoRender	77.0	73.0	70.0	16.0	75.0	57.0	92.0	69.0	3.0	40.0	39.0	87.0	58.2
VAoT	77.0	73.0	63.0	16.0	75.0	58.0	91.0	64.0	2.0	40.0	36.0	79.0	56.2
VAoT-WrongRender	76.0	71.0	63.0	20.0	73.0	52.0	75.0	54.0	4.0	42.0	33.0	84.0	53.9
Qwen3-VL-32B-Instruct													
CoT	30.0	20.0	29.0	20.0	63.0	31.0	69.0	51.0	2.0	35.0	49.0	65.0	38.7
VAoT-NoRender	31.0	18.0	28.0	21.0	59.0	25.0	71.0	45.0	4.0	35.0	48.0	61.0	37.2
VAoT	30.0	22.0	26.0	17.0	58.0	25.0	65.0	49.0	2.0	26.0	46.0	62.0	35.7
VAoT-WrongRender	33.0	16.0	30.0	18.0	63.0	30.0	47.0	33.0	4.0	34.0	42.0	67.0	34.8

unrelated content. It receives neither the reference answer nor a reasoning objective. The execution and intervention conditions are defined in Section 4.1.

VAoT is an inference-time diagnostic protocol and requires no access to the internals of the model.

4 Experiments

4.1 Experimental Setup

Models and coverage. We evaluate GPT-5.5, GPT-o3, Gemini 3.5 Flash, and Qwen3-VL-32B-Instruct under all four settings on the complete 1.2K-sample benchmark. Table 2 and Figure 5 report outcome results. Table 3 and Figure 6(a) cover all 4,800 VAoT trajectories. Figures 6(b), 7, and 8 use complete sample-level alignments across all four models. Additional statistics appear in Appendix D.

Inference settings. CoT reasons textually over the original image. VAoT-NoRender generates structured actions without executing them. VAoT executes the actions and returns rendered states, while VAoT-WrongRender returns natural-looking, task-relevant corrupted states as a diagnostic intervention.

Evaluation. We use normalized exact matching for structured answers and a semantic-equivalence judge for free-form predictions. For each VAoT trajectory, GPT-5.4 selects one key visual step and scores Action Relevance, Render Faithfulness, and Feedback Uptake on $\{0, 0.5, 1\}$. Model identity and explicit correctness labels are withheld. Full prompts and validation protocols appear in the appendix.

4.2 Main Results

Table 2 reports category-level accuracy on the complete 1.2K-sample benchmark. **No single inference setting dominates:** GPT-5.5 and Qwen3-VL-32B-Instruct perform best with CoT, GPT-o3 with VAoT, and Gemini 3.5 Flash with VAoT-NoRender. The effect of intermediate visual reasoning therefore depends on both the model and the task.

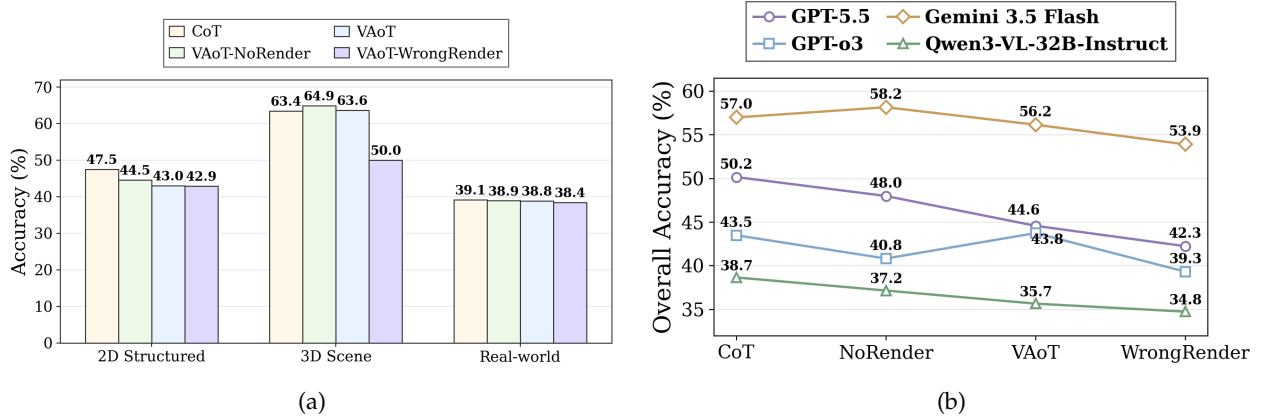


Figure 5 Visual-action reasoning across task groups and models. (a) Accuracy under the four inference settings, averaged across models within each task group. (b) Overall accuracy for each model and setting. All results use the complete 1.2K-sample benchmark.

Robot Manipulation is a consistent low-accuracy outlier. These tasks require precise target grounding and the immediate manipulation command. Selecting a nearby object, describing the scene, or returning a multi-step plan is counted as incorrect, leaving little room for visual actions to compensate for grounding errors.

Takeaway 1 Intermediate visual reasoning is a conditional capability rather than a universal accuracy booster: the strongest setting differs across model families.

4.3 When Does Visual Thinking Help?

Figure 5 summarizes the results by broad task group and by model.

Task regimes. Structured 2D problems favor direct reasoning over the original image, especially for geometry and visual puzzles. In 3D scenes, VAOt-NoRender is strongest on average, indicating that explicitly selecting objects and relations can organize relational reasoning even before an action is rendered. In real-world scenes, CoT, VAOt-NoRender, and VAOt are nearly tied on average, showing no clear aggregate advantage for a single reasoning strategy.

Model profiles. GPT-5.5 and Qwen3-VL-32B-Instruct exhibit *text-first* profiles, Gemini 3.5 Flash a *planner-first* profile, and GPT-o3 a slight *closed-loop* preference. Thus, models differ not only in final accuracy but also in the stage of visual reasoning from which they benefit.

Takeaway 2 Visual thinking changes regime across environments: direct perception leads on explicit 2D diagrams, action planning slightly leads in 3D scenes, and no single strategy has a clear aggregate advantage in real-world environments.

VAOt-WrongRender generally lowers accuracy, including cases in which VAOt does not outperform VAOt-NoRender. A model can therefore depend on returned visual feedback without obtaining a net gain from correct rendering.

Takeaway 3 Visual-state utility and visual-state dependence are not equivalent: correct rendering may yield little net gain, while corrupting the returned state can still cause measurable performance degradation.

Table 3 Process-level diagnosis on the complete VAOt trajectories. Average Action Relevance, Render Faithfulness, and Feedback Uptake across the three visual-reasoning groups and overall. Each dimension is scored on $\{0, 0.5, 1\}$ for one key visual step per trajectory. Each model contributes 1,200 trajectories.

Model	Metric	2D Structured	3D Scene	Real-world	Overall
GPT-5.5	Action Relevance	0.980	0.995	0.988	0.985
	Render Faithfulness	0.595	0.550	0.681	0.616
	Feedback Uptake	0.723	0.785	0.837	0.772
GPT-o3	Action Relevance	0.994	0.992	0.948	0.978
	Render Faithfulness	0.588	0.593	0.664	0.614
	Feedback Uptake	0.812	0.843	0.852	0.830
Gemini 3.5 Flash	Action Relevance	0.974	0.988	0.972	0.976
	Render Faithfulness	0.599	0.705	0.639	0.630
	Feedback Uptake	0.656	0.812	0.691	0.694
Qwen3-VL-32B-Instruct	Action Relevance	0.958	0.978	0.949	0.958
	Render Faithfulness	0.563	0.593	0.641	0.594
	Feedback Uptake	0.832	0.913	0.909	0.871

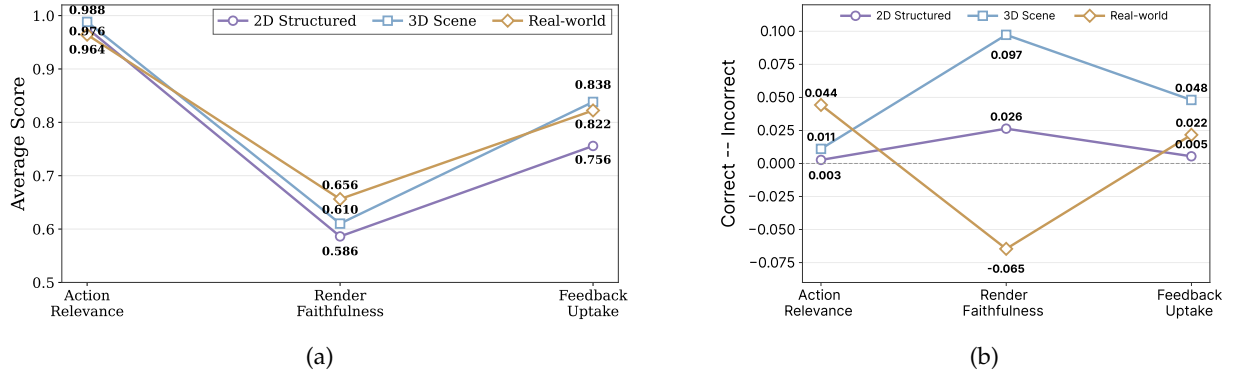


Figure 6 Process-level diagnosis across visual environments. (a) Average Action Relevance, Render Faithfulness, and Feedback Uptake across the three task groups, averaged over all four models. (b) Outcome-stratified correct-minus-incorrect differences in the three process scores, averaged over the four models.

4.4 Explaining Outcome Patterns through Process-level Diagnosis

To localize the source of the outcome differences, we decompose VAOt into three stages: *planning*, *rendering*, and *feedback use*. Action Relevance measures whether the requested operation targets relevant visual evidence; Render Faithfulness measures whether the operation is correctly realized; Feedback Uptake measures whether subsequent reasoning uses information from the returned visual state.

Action Relevance is consistently near saturation, whereas Render Faithfulness is substantially lower across all models and task groups. **The largest observed degradation therefore occurs after action selection:** a plausible visual plan must still be rendered accurately and incorporated into later reasoning. Qwen3-VL-32B-Instruct has the highest overall Feedback Uptake (0.871) despite lower final-answer accuracy, further illustrating that using returned visual information is distinct from using it correctly. The human audit in Section 4.5 evaluates the reliability of these automatic judgments.

Different visual environments fail at different stages. Figure 6(b) provides an outcome-stratified process analysis averaged over all four models. 3D scene reasoning has a pronounced correct-incorrect gap in Render Faithfulness (0.097), substantially larger than its Action Relevance (0.011) and Feedback Uptake (0.048) gaps. Real-world reasoning instead separates successful trajectories most clearly through Action Relevance (0.044), while its Render Faithfulness gap is negative (-0.065) and its Feedback Uptake gap is smaller (0.022). For 2D

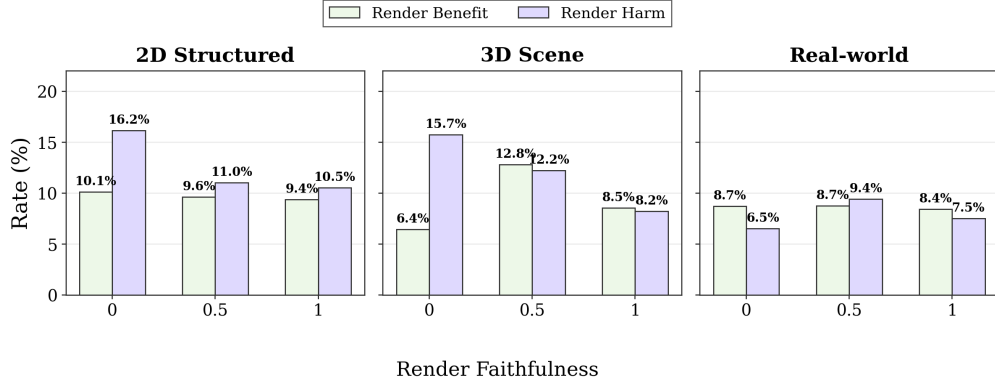


Figure 7 Rendering benefit and harm by Render Faithfulness. Benefit denotes a VAoT-NoRender incorrect-to-VAoT correct transition, and harm denotes the reverse. Rates are normalized within each task group and Render Faithfulness bin for the four-model aligned subset.

tasks, all three gaps remain small (at most 0.026), consistent with the original diagrams already exposing much of the required structure.

Takeaway 4 The main bottleneck is not selecting a task-relevant visual action. It lies in faithfully executing that action and using the resulting evidence, with the dominant failure stage varying across visual environments.

Complete correctness-split statistics are reported in Appendix E.

Rendering benefit and rendering harm. To separate opposing effects of rendered feedback, we compare aligned VAoT-NoRender and VAoT trajectories within each Render Faithfulness group. *Render benefit* is an incorrect-to-correct transition, and *render harm* is the reverse transition.

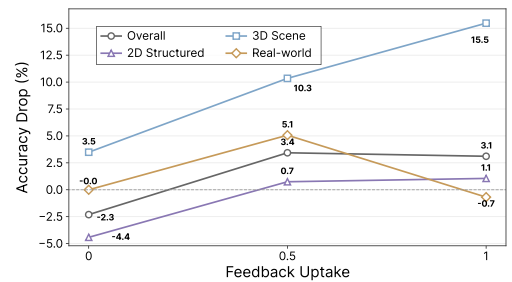
On the four-model aligned subset, Figure 7 shows that completely unfaithful rendering produces a negative transition balance in 2D and 3D reasoning (−6.1 and −9.3 percentage points, respectively), while the real-world group is slightly positive (2.2). Higher Render Faithfulness primarily reduces render harm. At score 1, the transition balance remains slightly negative in 2D (−1.2 points), but becomes mildly positive in 3D (0.3) and real-world reasoning (0.9).

Takeaway 5 Render Faithfulness mainly determines whether execution preserves or damages the planning gain: unfaithful renders are especially harmful in 2D and 3D reasoning, while more faithful renders mostly reduce disruption and shift the net balance toward neutral or mildly positive outcomes.

Feedback uptake and behavioral dependence. To test whether Feedback Uptake corresponds to observable dependence on the returned visual state, we align VAoT and VAoT-WrongRender trajectories and group them by the Feedback Uptake score assigned to the VAoT trajectory. We report $\text{Acc}_{\text{VAoT}} - \text{Acc}_{\text{WrongRender}}$, where larger positive values indicate greater sensitivity to corrupted feedback.

Overall accuracy degradation changes from −2.3 to 3.4 and 3.1 percentage points as Feedback Uptake rises from 0 to 0.5 and 1. **The relationship is strongest in 3D scene reasoning**, where the drop grows from 3.5 to 10.3 and 15.5 points.

Figure 8 Accuracy degradation under corrupted feedback. Results use complete sample-level alignments across all 1.2K samples for all four models; larger values indicate greater sensitivity.



The association is weaker or non-monotonic in 2D and real-world tasks, indicating that the behavioral validity of Feedback Uptake remains environment-dependent. Nevertheless, corrupted feedback changes the

semantic answer in 32.7–54.2% of samples across the four models, even when its net accuracy effect is smaller. Complete model-level counts are reported in Appendix 8.

Takeaway 6 Feedback Uptake tracks corrupted-feedback sensitivity most clearly in 3D reasoning, but the association remains environment-dependent.

4.5 Human Validation of Process-level Evaluation

Because the process analysis relies on an external multimodal judge, we conduct a diagnostically stratified human audit. Two human annotators review 240 VAOt trajectories drawn from a $4 \times 3 \times 4 \times 5$ design over GPT-5.5, GPT-o3, Gemini 3.5 Flash, and Qwen3-VL-32B-Instruct, three task groups, four diagnostic strata, and five samples per stratum.

For each trajectory, the annotators independently assess the selected key step and the three process scores as *reasonable*, *partially reasonable*, or *unreasonable*. Pooling their 480 ratings per target, 92.9–96.9% of judgments are at least partially reasonable across all four targets.

Table 4 Human alignment of process-level evaluation. Rates are pooled across two independent annotators (480 ratings per target).

Annotation target	Reasonable	Reasonable or partially reasonable
Key-step selection	88.3%	94.4%
Action relevance	74.8%	96.9%
Render faithfulness	70.2%	92.9%
Feedback uptake	79.6%	95.0%

The larger strict-to-partial gaps for Action Relevance and Render Faithfulness indicate disagreement mainly at the boundary between fully and partially supported judgments; pooled reasonable-or-partial rates exceed 92.9% for every target. Sampling, annotation details, and per-annotator human-validation results are provided in Appendix F.1. WrongRender quality-audit results and paired accuracy analyses on quality-filtered subsets are provided in Appendix F.2. The VAOt-WrongRender accuracy gap remains positive under both the strict and relaxed quality criteria, although its magnitude varies with intervention quality. Representative successful, diagnostic, and corrupted-feedback trajectories are shown in Appendix G.

5 Related Work

Multimodal chain-of-thought and active visual reasoning. Textual chain-of-thought has been extended from language reasoning to multimodal problem solving, with evaluations covering rationale quality, robustness, efficiency, and error localization [8, 28]. A rapidly growing line of work instead treats vision as an active reasoning workspace. Tool-based methods crop, zoom, annotate, sketch, or otherwise manipulate task-relevant image regions [7, 21, 30]. Interactive and generative approaches construct intermediate visual states during reasoning through image editing, visual generation, or interleaved text–visual inference [12, 15, 19, 20]. Recent work further explores continuous visual actions and repeated access to visual information during multimodal reasoning [6, 29]. Reliability-oriented approaches address noisy intermediate images or discrepancies between textual plans and executed visual actions [11, 25]. These methods demonstrate the potential of active visual reasoning, but performance improvements alone do not establish that a returned visual state faithfully realizes the intended action or is subsequently used by the model.

Benchmarks for visual intermediate states. MIRA studies tasks in which intermediate visualizations can facilitate reasoning, while ViC-Bench evaluates free-form visual-interleaved reasoning trajectories [23, 31]. TWI-PRMBench focuses on process reward modeling for thinking-with-images trajectories, and TwiFF-Bench evaluates dynamically generated future-frame reasoning [14, 32]. These benchmarks substantially broaden the evaluation of intermediate visual reasoning. However, they primarily measure the usefulness, plausibility, or overall quality of visual traces. They do not jointly diagnose whether a self-generated visual action

is task-relevant, whether the returned state faithfully realizes that action, and whether later reasoning behaviorally depends on the returned visual evidence.

Diagnosing visual-state use. Several recent studies move closer to evaluating whether intermediate visual information is faithful or answer-critical. Faithfulness-oriented evaluation examines whether generated visual thoughts are consistent with the intended reasoning process [16]. View Dropout encourages unified multimodal models to rely on generated thinking images by restricting direct information flow from the original views to the final answer [24]. Systematic comparisons of tool-based and tool-free agents further show that producing tool-call traces does not necessarily imply that the returned tool outputs expand the set of problems an agent can solve [3]. See2Think is complementary to these studies. Rather than introducing a training objective or comparing separately trained tool and non-tool agents, it provides a model-agnostic inference-time framework that records self-generated visual actions, externally rendered states, and subsequent reasoning. Matched standard and corrupted-render conditions then distinguish action relevance, render faithfulness, feedback uptake, visual-state utility, and behavioral dependence.

6 Conclusion and Limitations

We introduced **See2Think**, a unified framework for studying whether multimodal models genuinely use intermediate visual states during reasoning. See2Think combines **See2ThinkBench**, a benchmark of visually dependent reasoning problems evaluated through a unified answer-generation interface, and **VAoT**, an observable and intervenable protocol that records visual actions, rendered states, and subsequent reasoning. Experiments across GPT-5.5, GPT-o3, Gemini 3.5 Flash, and Qwen3-VL-32B-Instruct reveal that visual reasoning is model- and environment-dependent rather than governed by a single universally effective strategy. While models generally identify relevant visual operations, faithfully realizing these operations and using the returned visual evidence remain important bottlenecks. Controlled interventions further show that visual-state utility and behavioral dependence are distinct: a visual state may provide limited direct benefit while still strongly affecting model decisions when corrupted. By moving beyond the mere existence of visual traces and final-answer accuracy, See2Think provides a controlled framework for evaluating when “thinking with images” is genuine, useful, or misleading.

Limitations. First, our evaluation focuses on four representative multimodal models and may not capture the full diversity of current and future vision-language systems. Second, VAoT relies on an external rendering component and automatic process evaluation, which may introduce errors despite our human validation. Third, the measured effect of VAoT-WrongRender depends on intervention quality. Quality-filtered analyses on the human-audited subset preserve the direction of the accuracy drop, but its magnitude varies across filtering criteria. Future work may explore broader model coverage, learned rendering mechanisms, and more fine-grained process supervision for visual reasoning.

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A Benchmark Construction Details

This section provides additional implementation details for constructing See2ThinkBench. The benchmark construction consists of four stages: source dataset collection, caption-only visual-dependency filtering, answer-format conversion, and manual quality checking.

A.1 Source Dataset Collection and Preprocessing

We collect candidate samples from RBench-V [4], EMMA [5], M3CoT [2], PRISM-Bench [18], CLEVR [9], SuperCLEVR [13], VLABench [27], DROID [10], and IntPhys2 [1].

To enable unified evaluation, source-specific task names are mapped into the semantic categories used in See2ThinkBench:

- **2D structured reasoning:** Geometry, Spatial Puzzle, Physics, Chemistry, Science QA, and Abstract Pattern, instantiated from RBench-V, EMMA, M3CoT, and PRISM-Bench.
- **3D scene reasoning:** Object Attributes and Compositional 3D, instantiated from CLEVR and SuperCLEVR, respectively.
- **Real-world visual reasoning:** Robot Manipulation, Robot State Change, Visual Commonsense, and Intuitive Physics, instantiated from VLABench, DROID, M3CoT, and IntPhys2, respectively.

We retain original images whenever available and modify only the textual question and answer format. Before further processing, samples with missing images, duplicated content, invalid references, corrupted files, or insufficient visual evidence are removed.

A.2 Caption-Only Visual-Dependency Filtering

We apply caption-only filtering to remove samples that can be solved without direct access to the original image. For each candidate sample, a caption generator receives both the image and the question, but is instructed to describe only visually observable evidence without answering the question or introducing unsupported inference.

A reasoning model then receives only the question and the generated caption, while the original image is withheld. The model is queried five times. Samples that are answered correctly in at least three trials are considered caption-solvable and removed. Remaining samples are retained for subsequent processing.

This procedure reduces text-dominant samples while preserving visually dependent problems. It does not assume that all retained samples are impossible to solve from language priors, but filters cases where textual surrogates are sufficient.

Prompt for Detailed Image Caption Generation

System prompt:

You are a precise multimodal description model. Describe all visually observable information in the provided image that may be relevant to answering questions about it.

Include visible objects, attributes, text, geometric structures, spatial relations, diagram elements, and physical states. Do not answer the associated question and do not infer information that is not visibly supported.

User instruction prompt:

Question associated with the image:

{question}

Generate a detailed and objective description of the image.

Return only the image description.

[The original image is provided.]

Prompt for Caption-Only Solvability Testing

System prompt:

You are solving a visual-reasoning problem without access to the original image. You are given only the question and a textual image description. Use only the supplied information. Do not invent missing visual evidence.

User instruction prompt:

Question:

{question}

Image description:

{caption}

Reason carefully and return a concise final answer in the following format:

Final Answer: {answer}

A.3 Answer-Format Conversion

Many source datasets contain multiple-choice or template-based questions. Whenever possible, we remove textual answer-option lists and rewrite the question as a free-form query while preserving the original visual evidence and reasoning requirement. A small subset (127 of 1,200 samples) retains structured candidate sets inherited from source tasks because the alternatives themselves form part of the reasoning problem; these candidates may appear in the question text or as panels embedded in the original image. These instances are evaluated as structured-answer tasks, while the remaining 1,073 use free-form answers.

For samples selected for free-form conversion, the rewritten question must maintain a unique and reproducible reference answer. The conversion process does not introduce additional evidence, reveal the correct answer, or change the underlying task objective.

Prompt for Free-Form Question Rewriting

System prompt:

You are converting a visual multiple-choice question into a free-form question.

Preserve the original visual evidence and reasoning requirement. Remove the answer choices and rewrite the question so that it has a unique and concise answer.

Do not introduce new information. Do not reveal the correct option. Do not change the underlying task.

User instruction prompt:

Original question:

{original_question}

Answer options:

{options}

Correct answer:

{correct_answer}

Return:

Open-ended question: {rewritten_question}

Reference answer: {reference_answer}

[The original image is provided.]

A.4 Manual Quality Checking

After automatic processing, retained samples undergo manual review. Reviewers verify that the rewritten questions remain grounded in the images, the reference answers are uniquely supported, and the visual evidence is sufficient for answering the questions.

Samples are revised or removed if they contain ambiguous visual references, underspecified answers, inconsistent image-question pairs, or substantial text-only shortcuts.

Reviewers additionally verify that each sample naturally supports meaningful visual operations, including highlighting relevant objects, cropping regions, drawing auxiliary lines, or annotating visual relations.

B Inference Prompts and Implementation Details

B.1 Implementation Settings

We evaluate GPT-5.5, GPT-o3, Gemini 3.5 Flash, and Qwen3-VL-32B-Instruct. For each model, all four inference settings use the complete 1.2K-sample benchmark, the same original images, answer format, and interaction budget. The main category-level outcome table and Figure 5 use all 1,200 samples, while group-level aggregates are reported in Appendix D. Process scores use all 1.2K VAoT trajectories per model, for 4,800 trajectories in total. GPT-5.4 is used as the external answer and process judge.

The renderer receives the current image state and the structured action only. For faithful rendering, it is constrained to execute the requested operation and preserve unrelated content. VAoT and VAoT-WrongRender use the same reasoning prompt and interaction budget; WrongRender changes only the returned visual state. In all main experiments, the intervention uses the `modify_key` condition to alter task-relevant evidence while aiming to preserve a natural-looking appearance and the broad operation intent. The reasoning model is not informed that the feedback has been corrupted. Paired intervention analyses use complete sample-level alignments across all 1.2K samples for all four models, as described in Section 4.1.

B.2 Text-CoT Prompt

Prompt for Text-CoT

ROLE AND GOAL

You are a multimodal reasoning assistant.

Your goal is to solve the provided problem by explicitly analyzing the given image(s) and generating complete reasoning steps with final answer.

INSTRUCTIONS

Observe carefully:

- Carefully inspect the provided image before reasoning.
- Describe what you observe that is relevant to the problem (e.g., spatial relations, geometric shapes, labels, or quantities).

Analyze the context:

- Review the original problem and integrate both visual and textual information.
- Generate a complete step-by-step reasoning process.

Generate complete solution:

- Provide all logical steps needed to solve the problem.
- Each step should build upon the previous one.
- End with the final answer.

Visual reasoning requirement:

- Your reasoning must explicitly reference visual evidence from the image(s).
- If the image were removed, your reasoning should be incomplete.
- Each step should reference what you see in the image that drives your reasoning.

OUTPUT FORMAT

Your output must contain the following parts:

****Complete Solution:****

****Step 1 (Text):****

Visual Observation: [Describe what the image shows relevant to this step]

Reasoning: [Concise explanation of your reasoning for this step]

Calculation/Result: [Show calculations and intermediate results]

****Step 2 (Text):****

Visual Observation: [Describe what the image shows relevant to this step]

Reasoning: [Concise explanation of your reasoning for this step]

Calculation/Result: [Show calculations and intermediate results]

[... continue for all steps ...]

****Final Answer:****

[The final numeric or symbolic result, clearly boxed or highlighted]

SPECIAL NOTES

- Generate all reasoning steps needed to solve the problem completely.
- Each step must explicitly reference visual elements from the image.
- Use mathematical notation where appropriate.
- The solution should be self-contained and logically complete.

EXAMPLE OUTPUT

****Complete Solution:****

****Step 1 (Text):****

Visual Observation: The image shows a right triangle with hypotenuse labeled as 10 cm and one acute angle labeled as 30 degrees.

Reasoning: In a right triangle, the side opposite the 30 degrees angle is half the length of the hypotenuse.

Calculation/Result: Opposite side = 10 cm $\times$ $\sin(30 \text{ degrees})$ = 10 $\times$ 0.5 = 5 cm

****Step 2 (Text):****

Visual Observation: The adjacent side to the 30 degrees angle can be found using the Pythagorean theorem or cosine function.

Reasoning: Using the cosine function: adjacent side = hypotenuse $\times$ $\cos(30 \text{ degrees})$

Calculation/Result: Adjacent side = 10 cm $\times$ $\cos(30 \text{ degrees})$ = 10 $\times$ $(\sqrt{3}/2)$ = $5\sqrt{3}$ cm $\approx$ 8.66 cm

****Step 3 (Text):****

Visual Observation: The triangle has all three sides now determined.

Reasoning: The perimeter is the sum of all three sides.

Calculation/Result: Perimeter = 10 cm + 5 cm + $5\sqrt{3}$ cm = 15 + $5\sqrt{3}$ cm

****Final Answer:****

The perimeter of the triangle is 15 + $5\sqrt{3}$ cm

CONTEXT

{problem_statement}

YOUR TASK

Based on the context above, analyze the image(s) and generate a complete step-by-step solution with final answer, ensuring your reasoning depends explicitly on visual evidence.

B.3 VAoT Prompt

Prompt for VAoT

****ROLE AND OBJECTIVE****

You are an expert in ****Multimodal Chain-of-Thought Reasoning****. Your goal is to solve problems step-by-step, acting as both a ****logical reasoner**** and a ****visual designer****.

You have full autonomy to decide ****when**** a visual aid is **pedagogically essential** -- and ****how expressively**** to render it (e.g., callout labels, hand-drawn highlights), using publication-quality conventions.

```

**CORE PHILOSOPHY**

1. **Step-by-Step Logic**
    Each step must represent **one atomic deduction**. Never collapse multiple ideas.

2. **Visual Necessity (CRITICAL)**
    -> Generate a visual action **ONLY IF** it *uniquely enables understanding* that text alone cannot provide:
    - [YES] **Highlighting a specific region** (e.g., "stress concentration at joint")
    - [YES] **Tracing an irregular path** (e.g., "blood flow through capillary")
    - [YES] **Zooming on unreadable details**
    - [YES] **Showing spatial relationships**
    - [YES] **Disambiguating overlapping objects**
    -> **SKIP ACTION** for:
    - Pure calculation ("Sum forces: F1 + F2 = 10N")
    - Logical inference ("Since A > B and B > C, then A > C")
    - Summary/conclusion without new visual reference

3. **Clean & Expressive Communication**
    - Labels **MUST** be semantic: "Friction", not "Box[200,300]"
    - When a visual *is* generated, **leverage enhanced styles** if they improve clarity:
        - 'callout' for key concepts
        - 'jitter' for organic structures
        - Domain-appropriate 'theme' (e.g., 'biology' for cells)
    -> But **never add decoration without purpose**.

**INSTRUCTIONS**

1. **Analyze Context**
    Review 'Problem', 'Original Image', and 'Previous Steps'.

2. **Identify Next Step**
    What is the *single next* logical move?

3. **Determine Visual Necessity**

* **For Step 1**: Always output **Text Explanation + exactly one visual action object**.
    The 'action' array MUST contain exactly one item.
    Do **not** output Final Answer in Step 1.

* **For Step 2 and later**:

    * Default to **Text Explanation only**.
    * Generate another visual action only when it helps inspect a new region, new object, new path, or new spatial
      relation that was not already shown.
    * Do not draw again for pure calculation, restatement, or conclusion.
    * Across the whole solution, prefer 1-3 visual actions unless the problem clearly needs more.

4. **Design Visual Action (If Chosen)**
    Select the most effective tool -- and **optionally its expressive style**:

    | Use Case | Recommended Tool + Style |
    |-----|-----|
    | Critical concept needing emphasis | 'annotate' + "shape": "callout" + "shadow": true |
    | Irregular structure (vessel, river) | 'trace_highlight' + "jitter": true + "feather": "gradient" |
    | Hypothetical boundary | 'ellipse' + "dash": "dashed" |
    | Domain coherence | Add 'global_style': { "theme": "biology" } (once) |

**STRICT CONTENT RULES**

- **Coordinates**: Always normalized to **0-1000** scale.
- **Labels**: **NO** coordinates, brackets, scores, or units.
    - [NO] "Force [300,400]", "Mitochondrion (0.92)"
    - [YES] "Force", "Mitochondrion"
- **Safety**: If 'style'/'shape' fields are invalid -> renderer ignores them silently.

**AVAILABLE VISUAL ACTIONS**

| Action | Required | Optional Fields | Notes | |
|---|---|---|---|---|
| 'annotate' | | 'target', 'content' | 'shape', 'style' | 'shape': "box" (default), "ellipse", "callout" |
| 'trace_highlight' | | 'target', 'content' | 'style' | 'target': 3-5 spine points; 'style': '{jitter, feather, opacity}' |
| 'highlight' / 'mask' | | 'target' | 'style' | 'style': '{feather, texture}' |

```



```

| 'overlay_text' | 'target', 'content' | 'style' | 'style': '{font_weight, bg_adaptive}' |
| 'draw_line' | 'target', 'content' | 'style' | -- |
| 'ellipse' | 'target', 'content' | 'style' | -- |
| 'crop' / 'zoom' | 'target' | -- | -- |

**Global Style (Optional, Top-Level)**
Add once (e.g., Step 1) to set rendering context:
```json
"global_style": { "theme": "biology", "enable_decor": true }
```

**OUTPUT FORMAT (Strict)**

**Step N (Text):**
[A concise reasoning. Explain WHAT, WHY, and *whether visual is necessary*. Optionally suggest style/theme.]

> *Example:*
> *The capillary network is irregular and directional; a bounding box would misrepresent its flow. A trace highlight
  with gradient fade better conveys blood movement. Visual is necessary to show path topology.*

**Step N (Action Description):**
*(INCLUDE ONLY IF visual is deemed necessary)*

```json
{
 "step": N,
 "visual_rationale": "Why this tool/style? (e.g., 'callout for emphasis on key term')",
 "global_style": { "theme": "biology" },
 "action": [
 {
 "type": "trace_highlight",
 "target": [[320,210], [380,240], [450,260]],
 "content": "Capillary Flow",
 "style": { "jitter": true, "feather": "gradient" }
 },
 {
 "type": "annotate",
 "shape": "callout",
 "target": [300,200,340,240],
 "content": "O2 Exchange",
 "style": { "corner_radius": 6 }
 }
]
}
```

**RULES FOR TERMINATION**

- Continue until solution is complete.
- Final step:
  **Final Answer:** [The Answer]

**CONTEXT**
Problem:
{problem_statement}

Previous Steps:
{previous_steps}

**YOUR TASK**
Based on the context above, generate the single next step. Decide strictly whether a visual action is necessary for this
step.

```

B.4 VAoT-NoRender Prompt

Prompt for VAoT-NoRender

```

**ROLE AND OBJECTIVE**
You are an expert in Multimodal Chain-of-Thought Reasoning.

This is the VAoT-NoRender setting. You may propose visual actions, but the system will not render them. Therefore,
proposed actions are only action-text suggestions and must not be treated as new visual evidence.

```

```

**CORE RULES**

1. Generate only the single next step.
2. Each step should make one atomic reasoning move.
3. Reason only from the problem statement, the original image, and previous text steps.
4. You may propose a visual action when it would help, but do not claim it has been executed.
5. Do not say that a region is highlighted, zoomed, cropped, traced, or annotated unless that state was already present in the original image.
6. Do not use previous proposed actions as evidence.
7. For embodied control tasks, predict only the next immediate requested action.

**WHEN TO PROPOSE A VISUAL ACTION**
Propose a visual action only when it would clearly help locate a key region, trace a path, show a spatial relation, separate overlapping objects, or zoom into dense details.

Skip visual actions for pure calculation, logical inference, summary, or final answer.

**SUPPORTED VISUAL ACTIONS**
Use only these action types:
‘annotate’, ‘highlight’, ‘mask’, ‘trace_highlight’, ‘draw_line’, ‘ellipse’, ‘crop’, ‘zoom’, ‘overlay_text’.

Coordinates must be normalized to 0-1000. Labels must be semantic and human-readable.

**OUTPUT FORMAT**

**Step N (Text):**
[One concise reasoning step. State what is observed, why it matters, and whether a visual action would be useful.]

**Step N (Action Description):**
Include this block only if a visual action would be useful.

‘‘‘json
{
  "step": N,
  "render_policy": "no_render",
  "visual_rationale": "Why this proposed action would help, although it is not rendered.",
  "action": [
    {
      "type": "annotate",
      "target": [300, 200, 340, 240],
      "content": "Key Evidence"
    }
  ]
}
’’’

When ready, end with:

**Final Answer:** [The answer]

**CONTEXT**
Problem:
{problem_statement}

Previous Steps:
{previous_steps}

**YOUR TASK**
Generate the single next step. Remember: proposed actions are not rendered and must not be used as visual evidence.

```

B.5 WrongRender Intervention Prompt

VAoT-WrongRender uses the same reasoning prompt and interaction procedure as standard VAoT. The intervention is introduced only at the rendering stage: after the reasoning model proposes a visual action, the image editor receives the following prompt to generate a natural-looking but intentionally corrupted visual state. The main evaluation uses only the `modify_key` condition, which alters task-relevant visual evidence. The supported `modify_non_key` condition is not used in the experiments reported in this paper.

Prompt for WrongRender Intervention

You are an image interference expert. Your task is to modify the provided image according to the interference type.

Original problem: {problem}

Interference type: {interference_type}

Please modify this image according to the interference type:

1. If the interference type is `modify_key`, please modify key areas in the image so that it produces errors or misleading information in important aspects that affect problem solving.
2. If the interference type is `modify_non_key`, please modify background or non-key information in the image, keeping the important information correct but creating interference in secondary details.

Please analyze the image content, identify the key versus non-key elements for solving the problem, and apply appropriate modifications based on the interference type. The modified image should look natural but contain the intended interference.

C Detailed Evaluation Protocols

C.1 Final-Answer Evaluation

We first extract the final answer. Structured-answer outputs are evaluated by exact matching after deterministic normalization of case, whitespace, punctuation, unit formatting, and common numerical forms. Free-form predictions that require semantic comparison are judged against the reference answer with the following production prompt.

Prompt for Accuracy / Answer Evaluation

```
You are a strict answer evaluator for a multimodal reasoning benchmark. Judge whether the model's final answer is
semantically correct with respect to the reference answer.

Question:
{row.get("question", "")}

Reference answer:
{row.get("ground_truth", "")}

Model final answer:
{row.get("final_answer", "")}

Rules:
1. Ignore harmless formatting differences, units formatting, LaTeX wrappers, punctuation, and equivalent wording.
2. For math, accept algebraically equivalent expressions and numerically equivalent answers when the intended quantity
   matches.
3. For multiple-choice questions, accept either the correct option letter or the correct option text.
4. If the model gives extra claims that contradict the reference, mark it incorrect.
5. If the model answer is empty, evasive, or says it cannot answer, mark it incorrect.
6. Be strict about counts, directions, relations, and named entities.

Return only a JSON object with:
{{
  "correct": true or false,
  "reason": "brief explanation"
}}
```

C.2 Process-Level Evaluation

For every VAOt trajectory, the judge receives the question, reference answer, model final answer, and complete trajectory. The final response is provided because Feedback Uptake requires assessing whether information from the rendered visual state is incorporated into subsequent reasoning and the model's final response. The judge selects one key visual step and scores Action Relevance, Render Faithfulness, and Feedback Uptake on {0, 0.5, 1}. Model identity is withheld, and no explicit correct/incorrect label is supplied.

Prompt for Key-Step Selection and Process Evaluation

```
You are an expert evaluator for multimodal reasoning trajectories.

You will evaluate a Visual Action-of-Thought (VAOt) trajectory. The model solves a visual reasoning problem by
alternating between textual thoughts, visual actions, rendered visual states, and subsequent reasoning.

Your task is to evaluate ONLY the VAOt trajectory. Do NOT compare it with Text-CoT, VAOt-NoRender, or VAOt-WrongRender.

Question:
{question}

Ground-truth answer:
{ground_truth}

Model final answer:
{final_answer}

Trajectory:
{trajectory_text}
```

Please first select the key visual step, then evaluate that selected step along three dimensions.

1. Key Visual Step Selection:

Identify the single visual step that is most relevant to the final reasoning or most directly exposes the failure source.

If there is no effective visual operation, use null.

1. Action Relevance:

Does the model choose visual actions that are useful for solving the task?

Score 0 / 0.5 / 1.

- 1: The visual action directly targets task-relevant evidence and is useful for solving the question.
- 0.5: The visual action is partially relevant, weakly targeted, or contains unnecessary but not harmful operations.
- 0: The visual action is irrelevant, generic, decorative, or does not meaningfully support the task.

1. Render Faithfulness:

Are the rendered visual states faithful to the intended visual actions?

Score 0 / 0.5 / 1.

- 1: The rendered visual state faithfully executes the intended action.
- 0.5: The rendering partially matches the action, but has noticeable ambiguity, imprecision, or minor errors.
- 0: The rendering is missing, wrong, misleading, or inconsistent with the intended action.

1. Feedback Uptake:

Does the subsequent reasoning actually use the rendered visual states?

Score 0 / 0.5 / 1.

- 1: Subsequent reasoning clearly uses the rendered visual state as evidence.
- 0.5: Subsequent reasoning weakly or implicitly uses the rendered state, but still relies mostly on text priors.
- 0: Subsequent reasoning ignores the rendered state or continues independently of it.

Return ONLY valid JSON in the following format:

```
{
  "key_step_id": <step id or null>,
  "key_step_reason": "<short explanation>",
  "action_relevance": {
    "score": <0, 0.5, or 1>,
    "reason": "<short explanation>"
  },
  "render_faithfulness": {
    "score": <0, 0.5, or 1>,
    "reason": "<short explanation>"
  },
  "feedback_uptake": {
    "score": <0, 0.5, or 1>,
    "reason": "<short explanation>"
  },
  "overall_failure_source": "<action_relevance | render_faithfulness | feedback_uptake | none | unclear>",
  "summary": "<one-sentence diagnostic summary>"
}
```

C.3 Paired Intervention Analysis

We perform paired sample-level analysis for two comparisons:

- VAOt-NoRender $\rightarrow$ VAOt, which separates rendering benefit and rendering harm;
- VAOt $\rightarrow$ VAOt-WrongRender, which measures accuracy degradation under corrupted visual feedback.

For the first comparison, transition shares are normalized by all matched trajectories within each Render Faithfulness group. For the second, trajectories are grouped by Feedback Uptake and we report $\text{Acc}_{\text{VAOt}} - \text{Acc}_{\text{WrongRender}}$.

D Complete Outcome and Paired-Intervention Results

D.1 Complete 1.2K Outcome Results

Table 5 reports group-level aggregates for all four settings on the complete benchmark. The main paper reports the corresponding 12-category results on the same 1,200 samples; this table provides a compact summary by visual-reasoning environment.

D.2 Complete Paired-Intervention Statistics

Tables 6 and 7 provide the counts and common-denominator rates underlying Figures 7 and 8. Table 8 reports semantic answer changes between VAOt and VAOt-WrongRender. These paired statistics use all four evaluated models, for which complete sample-level alignment records are retained.

Table 5 Accuracy on the complete 1.2K-sample benchmark.

| Model | Setting | 2D | 3D | Real-world | Overall |
|-----------------------|------------------|-------|-------|------------|---------|
| GPT-5.5 | CoT | 55.33 | 52.50 | 41.25 | 50.17 |
| | VAoT-NoRender | 50.00 | 57.00 | 40.50 | 48.00 |
| | VAoT | 45.33 | 52.50 | 39.50 | 44.58 |
| | VAoT-WrongRender | 43.83 | 47.50 | 37.25 | 42.25 |
| GPT-o3 | CoT | 40.50 | 63.50 | 38.00 | 43.50 |
| | VAoT-NoRender | 36.50 | 64.00 | 35.75 | 40.83 |
| | VAoT | 36.67 | 67.50 | 42.50 | 43.75 |
| | VAoT-WrongRender | 36.83 | 48.00 | 38.75 | 39.33 |
| Gemini 3.5 Flash | CoT | 61.83 | 77.50 | 39.50 | 57.00 |
| | VAoT-NoRender | 61.33 | 80.50 | 42.25 | 58.17 |
| | VAoT | 60.33 | 77.50 | 39.25 | 56.17 |
| | VAoT-WrongRender | 59.17 | 64.50 | 40.75 | 53.92 |
| Qwen3-VL-32B-Instruct | CoT | 32.17 | 60.00 | 37.75 | 38.67 |
| | VAoT-NoRender | 30.33 | 58.00 | 37.00 | 37.17 |
| | VAoT | 29.67 | 57.00 | 34.00 | 35.67 |
| | VAoT-WrongRender | 31.67 | 40.00 | 36.75 | 34.75 |

Table 6 Rendering benefit and harm on the four-model aligned subset. Benefit and harm are percentages of all aligned trajectories within each task group and Render Faithfulness bin; Net is Benefit minus Harm.

| Task group | RF | n | Benefit (%) | Harm (%) | Net (pp) |
|---------------|-----|------|-------------|----------|----------|
| 2D Structured | 0 | 99 | 10.1 | 16.2 | -6.1 |
| | 0.5 | 1788 | 9.6 | 11.0 | -1.4 |
| | 1 | 513 | 9.4 | 10.5 | -1.2 |
| 3D Scene | 0 | 140 | 6.4 | 15.7 | -9.3 |
| | 0.5 | 344 | 12.8 | 12.2 | +0.6 |
| | 1 | 316 | 8.5 | 8.2 | +0.3 |
| Real-world | 0 | 46 | 8.7 | 6.5 | +2.2 |
| | 0.5 | 1008 | 8.7 | 9.4 | -0.7 |
| | 1 | 546 | 8.4 | 7.5 | +0.9 |

Table 7 Sensitivity to corrupted feedback on the four-model aligned subset. Accuracy Drop is $\text{Acc}_{\text{VAoT}} - \text{Acc}_{\text{WrongRender}}$.

| Task group | FU | n | VAoT Acc. (%) | Wrong Acc. (%) | Drop (pp) |
|---------------|-----|------|---------------|----------------|-----------|
| Overall | 0 | 607 | 42.2 | 44.5 | -2.3 |
| | 0.5 | 786 | 42.9 | 39.4 | +3.4 |
| | 1 | 3407 | 46.1 | 42.9 | +3.1 |
| 2D Structured | 0 | 385 | 41.6 | 46.0 | -4.4 |
| | 0.5 | 403 | 44.2 | 43.4 | +0.7 |
| | 1 | 1612 | 43.1 | 42.0 | +1.1 |
| 3D Scene | 0 | 86 | 54.7 | 51.2 | +3.5 |
| | 0.5 | 87 | 60.9 | 50.6 | +10.3 |
| | 1 | 627 | 65.2 | 49.8 | +15.5 |
| Real-world | 0 | 136 | 36.0 | 36.0 | -0.0 |
| | 0.5 | 296 | 35.8 | 30.7 | +5.1 |
| | 1 | 1168 | 39.9 | 40.6 | -0.7 |

Table 8 Semantic answer changes under corrupted feedback. Changed answers are determined by the semantic answer-change judge rather than direct string comparison.

| Model | Changed | Change Rate (%) |
|-----------------------|-------------|-----------------|
| GPT-5.5 | 624 / 1,200 | 52.0 |
| GPT-o3 | 607 / 1,200 | 50.6 |
| Gemini 3.5 Flash | 392 / 1,200 | 32.7 |
| Qwen3-VL-32B-Instruct | 650 / 1,200 | 54.2 |

E Complete Process Statistics

Table 9 reports the process scores used to compute the correct-minus-incorrect gaps in Figure 6(b). Counts correspond to VAoT final-answer outcomes for all four evaluated models on the complete benchmark.

Table 9 Process scores split by final-answer correctness. Action, Render, and Feedback denote Action Relevance, Render Faithfulness, and Feedback Uptake, respectively. Results use the complete four-model benchmark.

| Model | Answer | Group | Count | Action | Render | Feedback |
|-----------------------|-----------|------------|-------|--------|--------|----------|
| GPT-5.5 | Correct | 2D | 272 | 0.9798 | 0.6085 | 0.7610 |
| | | 3D | 105 | 0.9952 | 0.5905 | 0.7905 |
| | | Real-world | 158 | 0.9937 | 0.6646 | 0.8734 |
| | Incorrect | 2D | 328 | 0.9802 | 0.5838 | 0.6921 |
| | | 3D | 95 | 0.9947 | 0.5053 | 0.7789 |
| | | Real-world | 242 | 0.9835 | 0.6921 | 0.8140 |
| GPT-o3 | Correct | 2D | 220 | 0.9909 | 0.6091 | 0.8318 |
| | | 3D | 135 | 0.9963 | 0.6519 | 0.8815 |
| | | Real-world | 170 | 1.0000 | 0.6206 | 0.8529 |
| | Incorrect | 2D | 380 | 0.9961 | 0.5763 | 0.8000 |
| | | 3D | 65 | 0.9846 | 0.4692 | 0.7615 |
| | | Real-world | 230 | 0.9087 | 0.6957 | 0.8522 |
| Gemini 3.5 Flash | Correct | 2D | 362 | 0.9820 | 0.5994 | 0.6657 |
| | | 3D | 155 | 0.9871 | 0.7097 | 0.8161 |
| | | Real-world | 157 | 0.9904 | 0.5987 | 0.7389 |
| | Incorrect | 2D | 238 | 0.9622 | 0.5987 | 0.6408 |
| | | 3D | 45 | 0.9889 | 0.6889 | 0.8000 |
| | | Real-world | 243 | 0.9609 | 0.6646 | 0.6605 |
| Qwen3-VL-32B-Instruct | Correct | 2D | 178 | 0.9522 | 0.5843 | 0.8539 |
| | | 3D | 114 | 0.9912 | 0.6009 | 0.9386 |
| | | Real-world | 136 | 0.9779 | 0.5772 | 0.8824 |
| | Incorrect | 2D | 422 | 0.9609 | 0.5533 | 0.8223 |
| | | 3D | 86 | 0.9593 | 0.5814 | 0.8779 |
| | | Real-world | 264 | 0.9337 | 0.6742 | 0.9223 |

F Human Validation and WrongRender Quality Audit

F.1 Human Validation of Process Annotations

The human audit is a diagnostic reliability check rather than a second full annotation benchmark. Two annotators independently review the same 240 VAoT trajectories, sampled with a $4 \times 3 \times 4 \times 5$ design over GPT-5.5, GPT-o3, Gemini 3.5 Flash, and Qwen3-VL-32B-Instruct, three task groups, four diagnostic strata, and five trajectories per cell. The four strata are:

1. Action Relevance = 1 with an incorrect VAoT answer;
2. Action Relevance = 1 and Render Faithfulness = 0;
3. Action Relevance = 1 and Render Faithfulness = 0.5;
4. Action Relevance in $\{0, 0.5\}$.

This construction covers high-action/failed-answer cases, rendering failures, partial renders, and weak action selection across all audited models and environments.

For each trajectory, the annotators inspect the original image and question, the complete VAoT trajectory, the judge-selected key step, the three process scores, and the judge explanations. Each target is labeled *reasonable*, *partially reasonable*, or *unreasonable*. The main paper reports rates pooled across both annotators; the per-annotator summaries are shown in Table 10.

Table 10 Human-validation results by annotator. R denotes Reasonable; R/P denotes Reasonable or Partially Reasonable. Each annotator independently reviews the same 240 trajectories.

| Annotation target | A1 R | A1 R/P | A2 R | A2 R/P |
|---------------------|-------|--------|-------|--------|
| Key-step selection | 88.8% | 94.2% | 87.9% | 94.6% |
| Action relevance | 87.1% | 96.7% | 62.5% | 97.1% |
| Render faithfulness | 83.8% | 93.3% | 56.7% | 92.5% |
| Feedback uptake | 87.5% | 95.4% | 71.7% | 94.6% |

Human Review Instructions

You are reviewing an automatic evaluation of a visual-reasoning trajectory. For key-step selection, determine whether the selected step captures the visual operation most relevant to the final reasoning. For each process dimension, assess whether the score and explanation are supported by the complete trajectory.

Reasonable: the judgment is clearly supported.

Partially reasonable: the judgment captures the main behavior but is incomplete, imprecise, or slightly over- or under-scored.

Unreasonable: the judgment is contradicted by the trajectory or misses the central behavior.

For Feedback Uptake, credit only information that is actually present in the rendered state; do not infer uptake merely because the requested action is relevant.

The annotators differ most at the strict Reasonable-versus-Partially-Reasonable boundary for Action Relevance and Render Faithfulness. For every target, both annotators nevertheless mark more than 92% of judgments as at least partially reasonable.

F.2 WrongRender Quality Audit

We manually audit 120 VAoT-WrongRender cases. The original audit covers 90 cases sampled uniformly across GPT-5.5, GPT-o3, and Gemini 3.5 Flash and the three task groups, with 10 cases per model-group cell; we additionally audit 30 Qwen3-VL-32B-Instruct cases using the same task-group coverage. The audit examines whether a corrupted state changes task-relevant content in an incorrect direction while remaining plausible as an output from the same renderer. Each case is assessed along five criteria: corruption validity, visual plausibility, operation consistency, task relevance, and preservation of unrelated image content.

Human Audit Instructions for WrongRender

Inspect the original image, requested visual action, correct rendered state, and WrongRender state. For each criterion below, assign Pass, Partial, or Fail and briefly explain failed criteria.

- **Corruption validity:** task-relevant visual content is changed in an incorrect direction.
- **Plausibility:** the result resembles a plausible output from the same renderer.
- **Operation consistency:** the requested operation type is preserved.
- **Task relevance:** the corruption could affect reasoning for the question.
- **Content preservation:** unrelated image regions remain substantially unchanged.

A case receives the aggregate label **Strict Pass** when none of the five criteria is labeled Fail. It is considered **Acceptable** when at most one criterion is labeled Fail. Table 11 reports the aggregate quality rates before and after adding the 30 Qwen cases. The combined 120-case audit yields 56.7% Strict Pass and 78.3% Acceptable rates. The added Qwen cases are somewhat more reliable than the original three-model audit, with 76.7% Strict Pass and 86.7% Acceptable rates. We therefore treat WrongRender as an aggregate diagnostic

intervention rather than assuming that every corrupted state realizes the intended modification equally well.

Table 11 WrongRender quality-audit summary after adding Qwen.

| Subset | N | Pass (0 Fail) | Pass-or-Partial (≤ 1 Fail) |
|----------------|-----|----------------|----------------------------------|
| Original audit | 90 | 50.0% (45/90) | 75.6% (68/90) |
| Qwen addition | 30 | 76.7% (23/30) | 86.7% (26/30) |
| Combined | 120 | 56.7% (68/120) | 78.3% (94/120) |

Paired analysis on quality-filtered subsets. To examine whether the observed VAOt–WrongRender accuracy gap is driven primarily by failed corruptions, we recompute the paired accuracy difference on the combined 120-case human-audited set. The strict subset contains only cases with no failed audit criteria, while the relaxed subset allows at most one failed criterion. VAOt and VAOt-WrongRender are compared on the same samples within each subset.

Table 12 Paired accuracy on human-audited WrongRender subsets. Drop denotes $\text{Acc}_{\text{VAOt}} - \text{Acc}_{\text{WrongRender}}$ in percentage points.

| Subset | N | VAOt Acc. | WrongRender Acc. | Drop |
|-----------------------------|-----|-----------|------------------|------|
| Strict Pass (0 Fail) | 68 | 42.65 | 33.82 | 8.82 |
| Acceptable (≤ 1 Fail) | 94 | 41.49 | 38.30 | 3.19 |

The Qwen-only strict and acceptable subsets show accuracy drops of 8.70 and 7.69 percentage points, respectively. After combining all four models, the strict subset exhibits an 8.82-point drop, while the relaxed subset retains a positive 3.19-point drop. The behavioral-dependence result is therefore not restricted to interventions that fail the quality audit, but its estimated magnitude remains sensitive to intervention quality.

G Qualitative Trajectories

We provide representative trajectories spanning 2D structured, 3D scene, and real-world visual reasoning. The examples are selected to illustrate three complementary behaviors: successful visual-state use, process-level failures, and answer changes under corrupted feedback. All panels use the original model-produced images without redrawing.

G.1 Successful Visual-State Use

Figure 9 shows cases in which the requested action is task-relevant, faithfully rendered, and explicitly used in subsequent reasoning. Each trajectory receives Action Relevance, Render Faithfulness, and Feedback Uptake scores of 1.

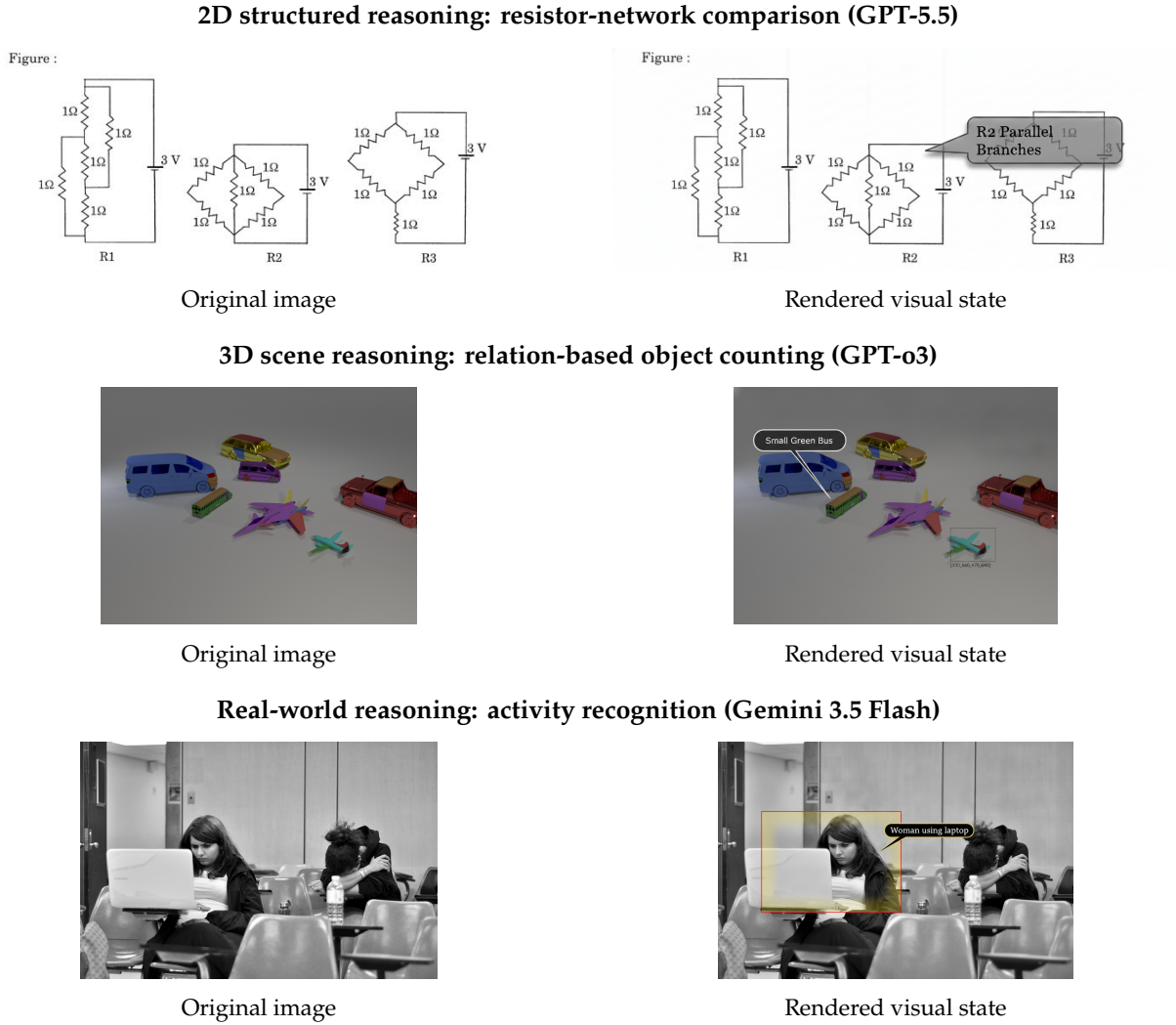


Figure 9 Representative successful VAOt trajectories. Top: highlighting the parallel branches supports equivalent-resistance reasoning. Middle: marking the target bus supports relation-based counting. Bottom: grounding the woman and laptop supports activity recognition.

G.2 Process-level Failure Cases

Figure 10 illustrates distinct failure modes after a relevant action is proposed. The 2D case is only partially rendered and partially used 1, 0.5, 0.5; the 3D case marks the wrong object and is not used reliably 1, 0, 0; and

the robot-manipulation case is only partially faithful and receives no measurable uptake 1, 0.5, 0, contributing to an incorrect continuous action prediction.

2D structured reasoning: convex-hull diagnosis (GPT-o3)



3D scene reasoning: material identification (Gemini 3.5 Flash)



Real-world reasoning: robot manipulation (GPT-5.5)

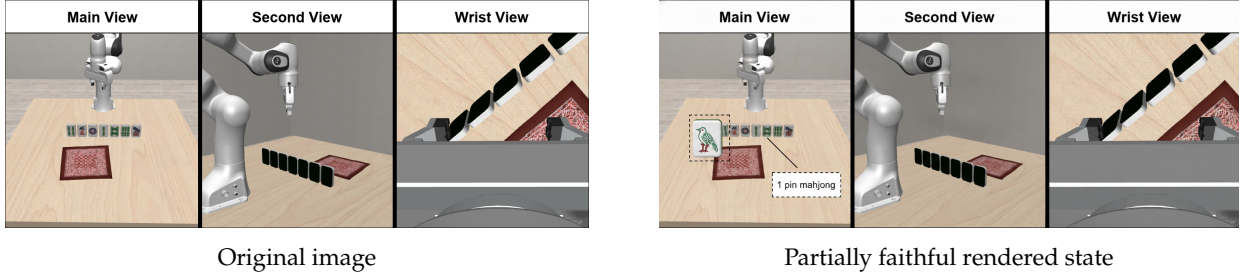
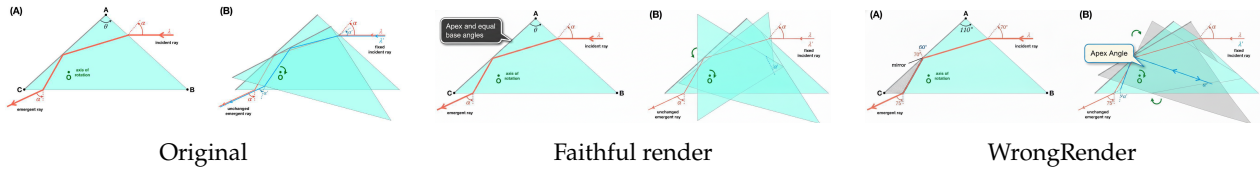


Figure 10 Representative process-level failure cases. The examples separate a relevant action proposal from the quality of its execution and subsequent use, illustrating why high Action Relevance alone does not guarantee a correct answer.

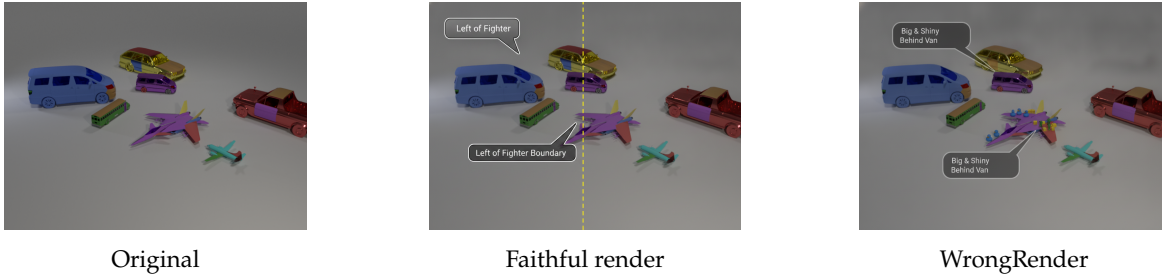
G.3 Answer Changes under WrongRender

Figure 11 compares the original image, faithful render, and corrupted render for one case from each environment. The interventions preserve the broad operation intent while altering task-relevant visual content: prism geometry in 2D, target relations in 3D, and branding on a tie in a real-world scene. In each case, the corrupted state changes the subsequent reasoning or final answer.

2D structured reasoning: prism geometry (GPT-5.5)



3D scene reasoning: relational object counting (GPT-o3)



Real-world reasoning: branded-tie interpretation (Gemini 3.5 Flash)

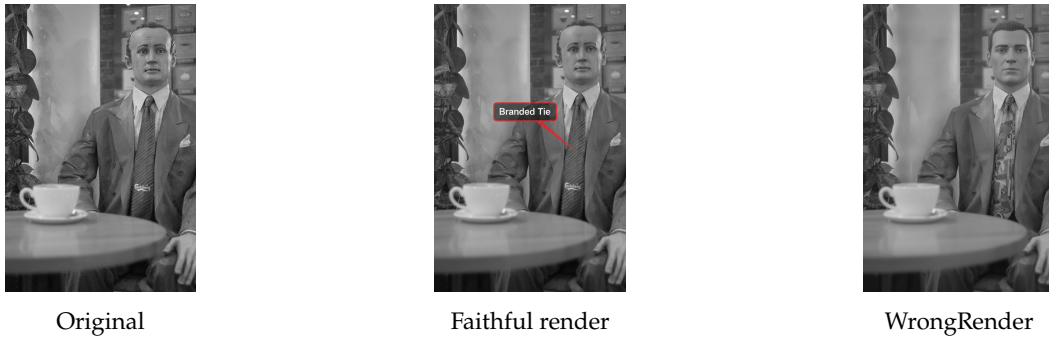


Figure 11 Representative WrongRender interventions. Top: the corrupted prism geometry changes the inferred refractive index. Middle: corrupted relation markers change the object count from 2 to 5. Bottom: replacing the branded tie with an unbranded pattern changes the interpretation from a promotional display to a decorative mannequin. These examples are qualitative illustrations; aggregate intervention quality is assessed separately by the human quality audit in Appendix F.2.