REASONING MODELS, NON-REASONING ANSWERS: UNCOVERING REASONING-BYPASS SHORTCUT IN ML-RMS

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ABSTRACT

Multimodal large reasoning models (MLRMs) aim to move multimodal large language models beyond *System-1-like* direct prediction toward explicit *System-2-like* reasoning for complex problems. However, recent studies reveal substantial inconsistency between the reasoning process and the final answer. Existing work often characterizes such behavior using concepts borrowed from human cognition, including hallucination, unfaithfulness, and even deception, but provides limited insight into its internal mechanism. In this work, we identify a prevalent yet underexplored pattern of reasoning inconsistency, termed Reasoning-Bypass Shortcut, in which the final answer specifically reverts to the prediction the model would have produced without reasoning. Across 7 MLRMs and 4 benchmarks, Reasoning-Bypass Shortcut accounts for 73.2% of all reasoning inconsistency cases, revealing a systematic tendency rather than random disagreement. To investigate its mechanism, we construct more than $6{,}000$ instances spanning diverse visual tasks that reliably capture this behavior. We then introduce *Reasoning Differential Probe* to localize representations associated with Reasoning-Bypass Shortcut, and further apply representation interventions to distinguish causal features from merely correlated ones. Our analysis reveals a sparse set of internal features that can redirect the model from its reasoning based decision (*System-2*) toward its direct prediction (*System-1*). Finally, we transfer our analysis to unseen scenarios and show that the identified internal signatures persist beyond the settings where they are first observed. This verifies the generality of our findings and shows that such behaviors can be captured from internal representations, complementing output-level observations with a mechanistic perspective. Code is available at this link.

1 INTRODUCTION

Recent post-training advances, particularly reinforcement learning (Sun et al., 2024; Huang et al., 2026; Zhang et al., 2025b; Wang et al., 2026b), have transformed multimodal large language models from predominantly direct-response systems into multimodal large reasoning models (MLRMs) capable of producing explicit intermediate reasoning before reaching an answer (Guo et al., 2025; Team et al., 2025; Jaech et al., 2024; Shao et al., 2024). This transition is often viewed through the analogy of human dual-process cognition (Evans, 2008): *System-1-like* inference directly maps perceptual inputs to responses through fast, pattern-driven computation, whereas *System-2-like* reasoning introduces an explicit deliberative process that progressively analyzes visual evidence and intermediate conclusions. Such reasoning substantially expands the ability of multimodal models to solve problems that require compositional visual understanding rather than immediate recognition (Zhang et al., 2025a).

Despite this apparent shift toward deliberative reasoning, an intriguing inconsistency remains: the generated reasoning process and the final prediction can disagree (Huang et al., 2025). Existing literature describes related phenomena using terms such as *unfaithful reasoning* (Panfilov et al., 2026; Yuan et al., 2026), *hallucination* (Wang et al., 2026a; Li et al., 2024b; Dong et al., 2026), and, under stronger assumptions, even *deception* (Wang et al., 2025a; Krishna et al., 2025). These concepts are largely borrowed from human epistemic and cognitive behavior to characterize the phenomenon at the behavioral level, yet offer limited insight into why such inconsistency emerges within the model.

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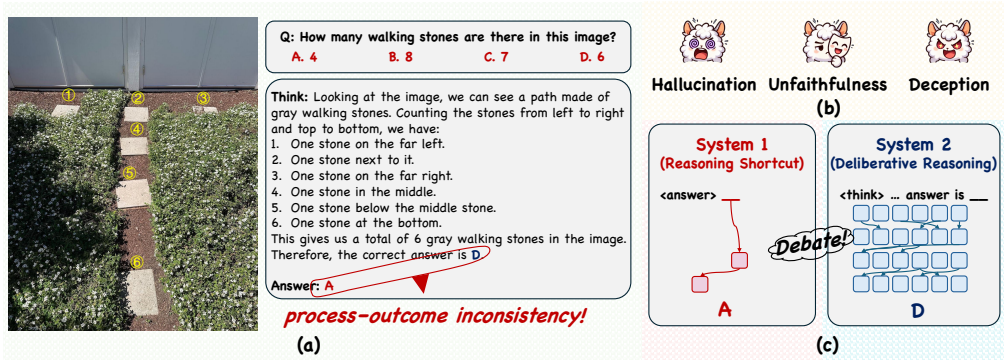

Figure 1: (a) An example of process-outcome inconsistency. (b) Existing behavioral interpretations. (c) Our internal mechanism perspective, which accounts for over 70% of these inconsistencies.

In particular, a fundamental question remains unanswered: *what internal mechanism causes a model to disregard its own preceding reasoning?*

A major line of work addresses this problem by explicitly encouraging faithful reasoning during post-training, for example through process-aware rewards (Chen et al., 2026; Maaz et al., 2025; Huang et al., 2025), supervision (Lightman et al., 2024), or auxiliary verification (Wang et al., 2024). While such approaches can mitigate inconsistent reasoning behavior, their effectiveness remains limited, and they typically require additional supervision or judging procedures and modify the model through further optimization. More importantly, suppressing the observed inconsistency does not by itself identify the internal mechanism that produces it. Understanding this mechanism is therefore important not only for mitigation, but also for determining why a model equipped with an explicit deliberative process can ultimately behave as if that process had never occurred.

In this work, we identify a prevalent yet underexplored pattern of process–outcome inconsistency, which we term **Reasoning-Bypass Shortcut**: despite reaching one conclusion through reasoning, the model overturns it at the answering stage and instead returns to the prediction it would have produced without reasoning. We identify a distinct set of internal representations associated with *System-1-like behavior*. When activated, these representations suppress the influence of the preceding reasoning trajectory and redirect the final decision toward the model's direct-answering behavior. This suggests that Reasoning-Bypass Shortcut reflects a tension between two prediction tendencies: a deliberative, *System-2-like* tendency expressed through explicit reasoning and a *System-1-like* direct-answer tendency that can re-emerge at the final prediction stage.

Specifically, our analysis follows an *output* $\rightarrow$ *internal* $\rightarrow$ *output* trajectory. We first characterize Reasoning-Bypass Shortcut at the output level by tracing the model's answers before, during, and after reasoning. We then turn to the internal representations and introduce *Reasoning Differential Probe* (**DiffProbe**), which contrasts representations before and after reasoning to localize features associated with Reasoning-Bypass Shortcut. Building on these features, we perform a set of causal activation interventions, including zero ablation, sign negation, and activation patching, to identify a sparse internal activation whose representations causally modulate the occurrence of Reasoning-Bypass Shortcut. Finally, we jointly compose the selected interventions and return to the output level, where the resulting intervention substantially suppresses Reasoning-Bypass Shortcut while largely preserving normal behavior. Negative controls and out of sample evaluations further validate the specificity and transferability of the identified representations.

We further analyze the relationship between Reasoning-Bypass Shortcut and task accuracy and find that, on Reasoning-Bypass Shortcut cases, the direct *System-1-like* prediction is often substantially more accurate than the conclusion reached through explicit *System-2-like* reasoning. Thus, although Reasoning-Bypass Shortcut exposes a clear failure of reasoning consistency, bypassing an unreliable reasoning trajectory can also recover correct predictions. This observation suggests a broader principle for reasoning models: ***models should learn not only how to reason, but also when not to reason.***

Our main contributions are summarized as follows:

- We identify and formalize **Reasoning-Bypass Shortcut**, a prevalent yet underexplored reasoning inconsistency in which the final answer reverts to the pre reasoning prediction. Across seven

MLRMs and four benchmarks, Reasoning-Bypass Shortcut accounts for 73.18% of all reasoning inconsistency cases.
- We introduce **DiffProbe** to localize attention head representations associated with Reasoning-Bypass Shortcut, and use causal activation interventions to distinguish causal features from correlated ones, revealing how System-1-like predictions can override System-2-like reasoning.
- Through joint interventions, negative controls, and out of sample evaluations, we validate the identified internal activations and show that manipulating it consistently suppresses Reasoning-Bypass Shortcut on unseen samples and datasets, improving reasoning and answer consistency.

2 Characterizing Reasoning-Bypass Shortcuts in MLRMs

In this section, we characterize Reasoning-Bypass Shortcut from the output perspective. We first define the scope of our study and provide a formal definition of Reasoning-Bypass Shortcut. We then evaluate seven recent MLRMs on four benchmarks, including VMCBench (Zhang et al., 2025c), MathVista (Lu et al., 2023), SEED-Bench (Li et al., 2024a), and MMT-Bench (Ying et al., 2024), which cover a broad range of capabilities from basic visual perception to complex reasoning. Detailed experimental settings, including configurations and prompt templates, are provided in Appendix B. The results show that Reasoning-Bypass Shortcut is a prevalent phenomenon rather than a model or dataset specific artifact. Key notations used throughout this work are summarized in Table 5.

2.1 From Reasoning Inconsistency to Reasoning-Bypass Shortcuts

Preliminary. We consider a multimodal large reasoning model $\mathcal{R}$ that takes a system prompt $\mathbf{X}_s$, visual input $\mathbf{X}_v$, and question $\mathbf{X}_q$ as input, where $\mathbf{X}_s$ contains the instruction that triggers explicit reasoning. Denoting the complete input as $\mathbf{X} = [\mathbf{X}_s, \mathbf{X}_v, \mathbf{X}_q]$, the model generates an explicit reasoning trace $\mathbf{r}$ followed by a final answer y:

$$\mathcal{R}(\mathbf{X}) = \texttt{<think>}\,\mathbf{r}\,\texttt{</think><answer>}\,y\,\texttt{</answer>}. \tag{1}$$

Reasoning Inconsistency. To extract the prediction expressed at different stages, existing studies typically employ an extractor $\mathrm{Ext}(\cdot)$, implemented either by rule-based parsing (e.g., regular expressions) (Yu et al., 2025) or LLM-as–judge (Zheng et al., 2023). Details of the extractor are provided in Appendix B.3. For clarity, we denote the prediction extracted from the reasoning trace as **mid** and that extracted from the final answer as **post**, representing the reasoning-stage conclusion and final prediction, respectively. Existing studies on reasoning inconsistency primarily focus on the following paradigm:

$$\textbf{mid} \neq \textbf{post}, \qquad \text{where } \textbf{mid} = \mathrm{Ext}(\mathbf{r}), \quad \textbf{post} = \mathrm{Ext}(y). \tag{2}$$

Our Scope and Formulation. Our characterization builds on two key observations. First, at any point during reasoning, a partial reasoning trace induces a conditional answer preference. Rather than treating this preference as latent, we elicit it by terminating the reasoning at that point and forcing the model to answer. Specifically, let the complete reasoning trace be $\mathbf{r} = (r_0, \ldots, r_{T-1})$ and $\mathbf{r}_{<t} = (r_i)_{i<t}$ denote its prefix before step t. We prefill $\mathbf{r}_{<t}$ within the reasoning field, close the reasoning, and prompt the model to answer:

$$y'_t = \mathrm{Ext}(\mathcal{R}(\mathbf{X} \oplus \texttt{<think>}\mathbf{r}_{<t}\texttt{</think><answer>})), \qquad 0 \le t \le T. \tag{3}$$

Here, y'_t represents the answer preferred by the model after observing the first t reasoning steps. Repeating this operation throughout the reasoning process yields an answer trajectory $(y'_0, \ldots, y'_T)$.

Second, the two endpoints admit natural interpretations under the *System-1/System-2* view. At $t = 0$, no reasoning has been provided, and the resulting prediction corresponds to the pre-reasoning prediction (**pre**). At $t = T$, the complete reasoning trace has been provided, recovering the post-reasoning prediction (**post**):

$$\begin{aligned} \underbrace{y'_0}_{\textbf{pre}} &= \mathrm{Ext}(\mathcal{R}(\mathbf{X} \oplus \texttt{<think></think><answer>})), \\ \underbrace{y'_T}_{\textbf{post}} &= \mathrm{Ext}(\mathcal{R}(\mathbf{X} \oplus \texttt{<think>}\mathbf{r}\texttt{</think><answer>})). \end{aligned} \tag{4}$$

We therefore use **pre** $= y'_0$ as an operational proxy for the model's *System-1-like* prediction, while **post** $= y'_T$ denotes the prediction after the complete *System-2-like* reasoning process. We also provide the detailed evolution of y'_t over the reasoning process in Appendix C.2.2.

Above, we define **pre**, **mid**, and **post** as the model's answers at different stages of reasoning. For MLRMs, our scope naturally excludes cases where **pre** $=$ **mid** $=$ **post**, since the model reaches the same prediction without relying on a non-trivial reasoning trajectory.

Reasoning-Bypass Shortcuts. We identify a distinctive pattern of Eq. (2) that is prevalent across MLRMs: the post-thinking answer frequently reverts to the pre-thinking prediction, i.e.,

$$\textbf{pre} = \textbf{post}, \qquad \text{subject to Eq. (2).} \tag{5}$$

To demonstrate that Reasoning-Bypass Shortcut is prevalent in existing MLRMs, we report two metrics. **Reasoning Inconsistency (RI%)** measures the proportion of samples satisfying Eq. (2), while **RBS/RI%** measures the proportion of Reasoning-Bypass Shortcut among all RI cases.

Key Takeaway 1. As shown in Table 1, Reasoning-Bypass Shortcut is prevalent across 7 MLRMs and 4 datasets, accounting for an average of 73.18% of reasoning inconsistency cases.

Table 1: Prevalence of reasoning inconsistency and Reasoning-Bypass Shortcuts across different MLRMs and benchmarks.

Model	VMC-Bench		MathVista		SEED-Bench		MMT-Bench	
	RI	RBS/RI	RI	RBS/RI	RI	RBS/RI	RI	RBS/RI
MM-Eureka	5.78%	69.86%	4.11%	100.00%	3.76%	78.26%	7.89%	58.00%
Ocean-R1	54.90%	85.23%	39.06%	83.80%	68.24%	89.95%	37.81%	84.73%
ORSTA	27.76%	71.47%	23.43%	71.64%	36.52%	83.11%	35.52%	69.82%
R1-OneVision	6.68%	50.59%	3.97%	30.77%	7.02%	78.00%	5.27%	51.85%
GThinker	12.74%	73.33%	7.56%	61.46%	16.93%	86.94%	10.15%	78.38%
Spatial-SSRL	12.24%	66.67%	10.69%	71.60%	22.22%	83.37%	21.62%	62.59%
Vlaa-Thinker	18.88%	81.08%	11.89%	77.01%	21.41%	87.26%	15.27%	62.16%

3 Understanding Reasoning-Bypass Shortcut from Internal Representations

In Section 2, we defined Reasoning-Bypass Shortcut and established its prevalence across different MLRMs. In this section, we investigate the internal mechanism underlying this behavior. Our analysis identifies a sparse set of representations associated with a *System-1-like* reasoning. Activating these representations substantially increases the probability of the answer that the model would produce without explicit reasoning. To uncover these representations, we first construct a balanced dataset in which internal activations serve as explanatory variables and the occurrence of Reasoning-Bypass Shortcut serves as the binary target. We then introduce *Reasoning Differential Probe (**DiffProbe**)* to identify heads whose representations exhibit distinct changes when Reasoning-Bypass Shortcut occurs. Finally, we intervene on the identified representations to isolate those that causally affect Reasoning-Bypass Shortcut. Representative Reasoning-Bypass Shortcut cases for each evaluated model are provided in Appendix D.

Data Construction. We construct a balanced dataset containing equal numbers of normal samples and samples exhibiting Reasoning-Bypass Shortcut. Let $z_i \in \{0, 1\}$ denote the behavioral label of sample i, where $z_i = 1$ indicates the occurrence of Reasoning-Bypass Shortcut and $z_i = 0$ denotes normal behavior. The resulting dataset is

$$\mathcal{D} = \{(\mathbf{x}_i, z_i)\}_{i=1}^{N}, \qquad |\mathcal{D}_{z=0}| = |\mathcal{D}_{z=1}|. \tag{6}$$

The feature $\mathbf{x}_i$ is constructed from the model's internal representations at the two decision points corresponding to y'_0 and y'_T in Eq. 4. Specifically, for the h-th attention head in layer ℓ, we extract the representation at the decision position immediately before answer generation:

$$\mathbf{h}_{i,t}^{(\ell,h)} = \mathrm{Head}_{\mathcal{R}}^{(\ell,h)}(\mathbf{X}_i \oplus \texttt{<think>}\mathbf{r}_{i,<t}\texttt{</think><answer>})_{-1}, \qquad t \in \{0, T\}, \tag{7}$$

where $\text{Head}_{\mathcal{R}}^{(\ell,h)}(\cdot)_{-1} \in \mathbb{R}^{d_h}$ denotes the representation of attention head h in layer ℓ at the final input position. Accordingly,

$$\mathbf{h}_{i,\text{pre}}^{(\ell,h)} = \mathbf{h}_{i,0}^{(\ell,h)}, \qquad \mathbf{h}_{i,\text{post}}^{(\ell,h)} = \mathbf{h}_{i,T}^{(\ell,h)}. \tag{8}$$

We collect these representations from `Ocean-R1`, `ORSTA`, and `Vlaa-Thinker`, the three models with the highest prevalence of Reasoning-Bypass Shortcut, on VMCBench, MMT-Bench, and SEED-Bench, resulting in a total of **6,132** samples. The answer distributions of mid and post for label-1 samples are provided in Appendix C.2.1.

3.1 Reasoning Differential Probe (DiffProb)

Probing is commonly used to test whether a target behavior or capability is encoded in a model's internal representations. A standard approach trains a lightweight classifier on internal activations to distinguish examples with and without the target property (Alain & Bengio, 2017; Li et al., 2023). In behavioral analysis, contrastive examples are particularly useful because they reduce information shared by the two conditions and emphasize representation changes associated with the target behavior (Rimsky et al., 2024).

However, directly probing a single representation is not well suited to Reasoning-Bypass Shortcut. The occurrence of Reasoning-Bypass Shortcut is not determined by a static state at either pre or post alone, but by how the model's internal state changes after reasoning. Moreover, an absolute head representation may encode substantial information unrelated to Reasoning-Bypass Shortcut, such as visual content, question semantics, and answer identity. We therefore introduce *Reasoning Differential Probe* ***(Diffprobe)***, which characterizes the reasoning induced change within the same sample. For attention head h at layer ℓ, we define its differential representation as

$$\Delta\mathbf{h}_i^{(\ell,h)} = \mathbf{h}_{i,\text{post}}^{(\ell,h)} - \mathbf{h}_{i,\text{pre}}^{(\ell,h)} = \mathbf{h}_{i,T}^{(\ell,h)} - \mathbf{h}_{i,0}^{(\ell,h)}. \tag{9}$$

This within sample difference suppresses information that remains stable before and after reasoning, while retaining the representation shift induced by the reasoning process.

Following the standard linear probing formulation (Alain & Bengio, 2017), we train an independent binary probe for each attention head. Let $\boldsymbol{\theta}^{(\ell,h)}$ and $b^{(\ell,h)}$ denote the probe parameters. The probability that sample i exhibits Reasoning-Bypass Shortcut is

$$p_i^{(\ell,h)} = P\left(z_i = 1 \mid \Delta\mathbf{h}_i^{(\ell,h)}\right) = \sigma\left(\boldsymbol{\theta}^{(\ell,h)\top} \Delta\mathbf{h}_i^{(\ell,h)} + b^{(\ell,h)}\right), \tag{10}$$

where $\sigma(\cdot)$ denotes the sigmoid function. The probe is optimized using binary cross entropy (Pham & Nguyen, 2024):

$$\boldsymbol{\theta}^{(\ell,h)*}, b^{(\ell,h)*} = \arg\min_{\boldsymbol{\theta},b} -\frac{1}{N}\sum_{i=1}^{N}\left[z_i \log p_i^{(\ell,h)} + (1-z_i)\log\left(1-p_i^{(\ell,h)}\right)\right]. \tag{11}$$

To validate the effectiveness of **DiffProbe**, we compare it with a conventional probe that predicts Reasoning-Bypass Shortcut from **post** decision-state representation. As shown in Table 2, DiffProbe consistently provides stronger signals for identifying attention heads associated with Reasoning-Bypass Shortcut, and the resulting head-wise importance distributions are shown in Fig. 2.

Table 2: AUROC comparison between the conventional Probe and our DiffProbe across different MLRMs and benchmarks. Results are reported as mean ± standard deviation over 10 seeds.

Model	VMC-Bench		SEED-Bench		MMT-Bench	
	Probe	DiffProbe	Probe	DiffProbe	Probe	DiffProbe
`Ocean-R1`	0.7842 ± 0.0316	0.8675 ± 0.0180	0.7530 ± 0.0246	0.8116 ± 0.0146	0.8369 ± 0.0193	0.8447 ± 0.0263
`ORSTA`	0.8734 ± 0.0312	0.8970 ± 0.0169	0.8839 ± 0.0120	0.9000 ± 0.0136	0.8657 ± 0.0192	0.8826 ± 0.0306
`VLAA-Thinker`	0.9136 ± 0.0154	0.9309 ± 0.0151	0.9180 ± 0.0133	0.9354 ± 0.0081	0.9307 ± 0.0139	0.9622 ± 0.0156

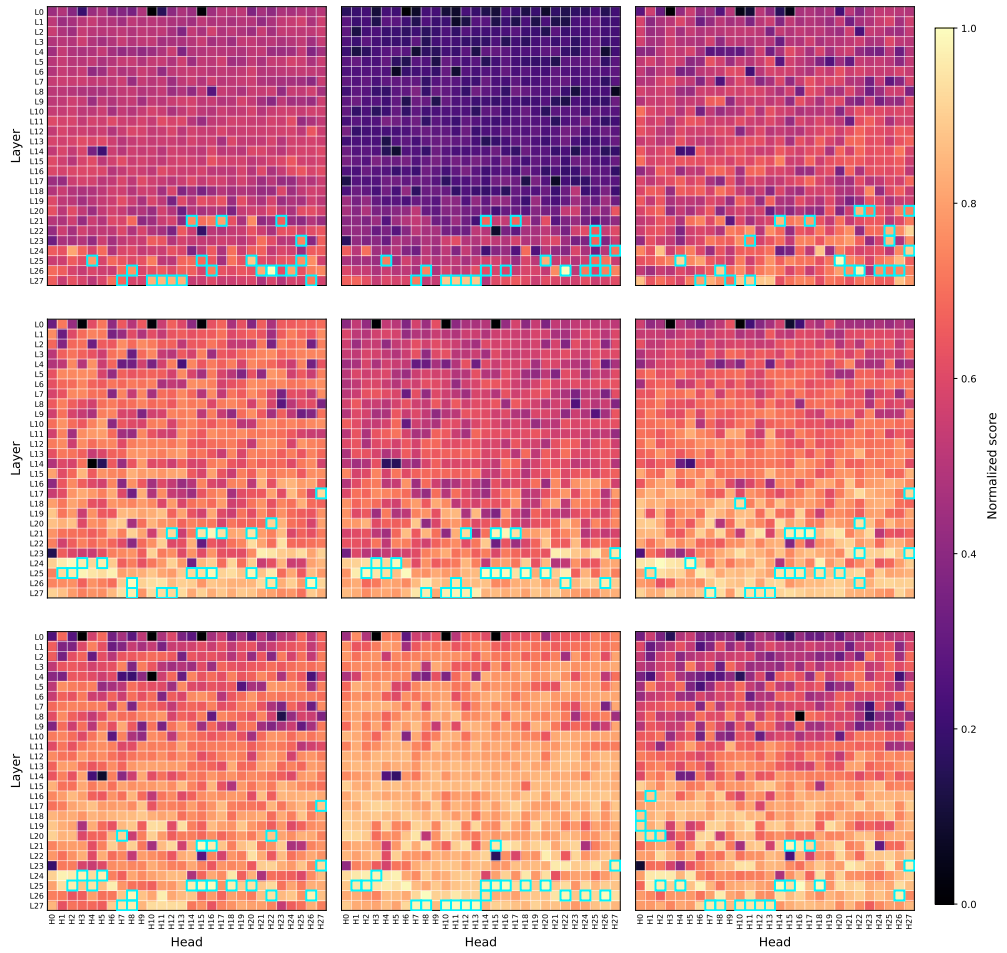

Figure 2: Head-level DiffProbe importance. The top-K heads are highlighted by cyan boxes.

Key Takeaway 2. As shown in Fig. 2, top-K heads exhibit consistent importance patterns across datasets within the same model, suggesting that Reasoning-Bypass Shortcut is associated with cross-dataset internal representations.

3.2 Causal Activation Intervention

The **DiffProbe** provides a coarse grained localization of attention heads associated with Reasoning-Bypass Shortcut, but leaves two questions unresolved. First, probing establishes statistical association rather than causality, and therefore cannot determine whether the identified heads actually influence the occurrence of Reasoning-Bypass Shortcut. Second, the functional direction of each head remains unclear, namely whether its activation promotes or suppresses Reasoning-Bypass Shortcut. To further investigate these effects, we perform *causal activation interventions* (Zhang & Nanda, 2024) on the identified attention heads. Specifically, we manipulate their representations through zero ablation, sign negation, and activation patching, and measure the resulting changes in output logits. This allows us to further isolate attention heads that causally affect Reasoning-Bypass Shortcut and determine the direction of their effects.

Specifically, for each attention head identified by DiffProbe, we intervene on its representation at the post-thinking decision point and measure the resulting change in output logits. Let $\mathbf{h}_{i,\text{post}}^{(\ell,h)}$ denote the representation of head h in layer ℓ for sample i at the post-thinking decision point. We define a unified intervention operator $\mathcal{I}_m(\cdot)$ as

$$\tilde{\mathbf{h}}_{i,\text{post}}^{(\ell,h)} = \mathcal{I}_m\left(\mathbf{h}_{i,\text{post}}^{(\ell,h)}\right), \qquad m \in \{\text{Zero}, \text{Neg}, \text{Patch}\}, \tag{12}$$

where

$$\mathcal{I}_m\left(\mathbf{h}_{i,\text{post}}^{(\ell,h)}\right) = \begin{cases} \mathbf{0}, & m = \text{Zero}, \\ -\mathbf{h}_{i,\text{post}}^{(\ell,h)}, & m = \text{Neg}, \\ \mathbf{h}_{i,\text{pre}}^{(\ell,h)}, & m = \text{Patch}. \end{cases} \tag{13}$$

Inspired by prior work showing that model behaviors can be represented and manipulated through directions in activation space (Arditi et al., 2024), we use three complementary interventions to examine the causal role of the identified *System-1-like* representations. **Zero** ablation removes the head representation to test whether it is necessary for maintaining the shortcut. **Neg** reverses its representation direction to examine whether its effect is directional. **Patch** restores the post-thinking representation to its paired pre-thinking state, testing whether the shortcut is progressively constructed during reasoning.

Intervention Effects and Causal Tuple Selection. For each intervention, we quantify its effect from both normal behavior and Reasoning-Bypass Shortcut. Let $c = (\ell, h, m)$ denote an intervention tuple, where ℓ, h, and m specify the layer, attention head, and intervention operator, respectively. Let $\mathbf{g}_i$ and $\widetilde{\mathbf{g}}_i^c$ denote the output logits before and after intervention c.

For normal samples with $z_i = 0$, we measure the predictive entropy $H(\text{softmax}(\mathbf{g}_i))$ to quantify the model's output confidence. For Reasoning-Bypass Shortcut samples with $z_i = 1$, we measure the logit margin between the reasoning conclusion mid_i and the direct prediction pre_i. We define the corresponding intervention effects as

$$\begin{aligned} \Delta_{\text{conf},i}^c &= H(\text{softmax}(\mathbf{g}_i)) - H(\text{softmax}(\widetilde{\mathbf{g}}_i^c)), && z_i = 0, \\ \Delta_{\text{RBS},i}^c &= [\widetilde{g}_i^c(\text{mid}_i) - \widetilde{g}_i^c(\text{pre}_i)] - [g_i(\text{mid}_i) - g_i(\text{pre}_i)], && z_i = 1. \end{aligned} \tag{14}$$

A positive Δ_{conf} indicates reduced predictive entropy and therefore increased confidence on normal samples. A positive Δ_{RBS} indicates that the intervention shifts the output logits from pre toward mid, thereby suppressing Reasoning-Bypass Shortcut.

Our goal is to identify intervention tuples that specifically modulate Reasoning-Bypass Shortcut, rather than merely increasing or decreasing output confidence in general. If the two effects have opposite signs, the intervention is more consistent with a nonspecific confidence effect, since it strengthens the currently dominant prediction without consistently favoring the reasoning conclusion. We therefore retain tuples whose averaged effects over the two behavioral groups have the same sign. Specifically, from the top-K heads ranked by DiffProbe, we define

$$\mathcal{C} = \left\{ c = (\ell, h, m) \;\middle|\; \begin{array}{l} (\ell, h) \in \text{Top-K}, \quad m \in \{\text{Zero}, \text{Neg}, \text{Patch}\}, \\ \overline{\Delta}_{\text{conf}}^c \cdot \overline{\Delta}_{\text{RBS}}^c > 0 \end{array} \right\}, \quad \begin{aligned} \overline{\Delta}_{\text{conf}}^c &= \frac{1}{|\mathcal{D}_0|} \sum_{i \in \mathcal{D}_0} \Delta_{\text{conf},i}^c, \\ \overline{\Delta}_{\text{RBS}}^c &= \frac{1}{|\mathcal{D}_1|} \sum_{i \in \mathcal{D}_1} \Delta_{\text{RBS},i}^c. \end{aligned} \tag{15}$$

Here, $\mathcal{D}_0$ and $\mathcal{D}_1$ denote the normal and Reasoning-Bypass Shortcut subsets, respectively. Positive values for both terms identify interventions that maintain or improve confidence on normal samples while suppressing Reasoning-Bypass Shortcut. Conversely, jointly negative values reveal the opposite causal direction. In both cases, the same sign criterion distinguishes behavior specific effects from generic confidence modulation. A detailed head by head analysis is provided in Appendix C.3.

Joint Intervention and Controls. After obtaining $\mathcal{C}$, we jointly apply the selected intervention tuples to test whether their individual causal effects compose at the model level. Following the definitions in Eq. 14, we denote the corresponding joint effects as $\overline{\Delta}_{\text{conf}}^{\mathcal{C}}$ and $\overline{\Delta}_{\text{RBS}}^{\mathcal{C}}$. This design is motivated by prior work showing that coordinated interventions over a sparse set of selected heads can produce consistent behavioral changes (Li et al., 2023). In addition, we report the answer flip rates on both the $z = 1$ set (FR_1) and the $z = 0$ set (FR_0). FR_1 measures, among samples exhibiting Reasoning-Bypass Shortcut, how often the intervention changes the final answer from pre to mid. In contrast, FR_0 quantifies the perturbation on normal samples by measuring how often a consistent post answer is changed to an inconsistent alternative.

To establish that the observed effect is specific to the identified representations and generalizes beyond the samples used for discovery (**Ours**), we conduct two negative controls and two out of sample

evaluations. For the first negative control, **Gaussian Noise**, we replace the intervention operator m of each tuple $c = (\ell, h, m) \in \mathcal{C}$ with Gaussian noise while keeping the identified layer and head unchanged. This tests whether the observed effect can be reproduced by nonspecific perturbations at the same representations. For the second negative control, **Random-K**, we replace each selected head h with a randomly sampled head outside the DiffProbe top-K from the same layer ℓ, while preserving the original intervention operator m. This controls for effects arising from the intervention itself rather than the identified heads. For generalization, **Held-Out** evaluates the same intervention tuples $\mathcal{C}$ on unseen samples from the original benchmarks, while **Cross-Dataset** applies them to Reasoning-Bypass Shortcut samples from MathVista (Lu et al., 2023), which are **unseen** during both probing and intervention. The results are reported in Tables 3 and 4.

Table 3: Generalization of the selected causal interventions across different evaluation settings. **Ours** denotes samples used for intervention tuple selection, **Held Out** denotes unseen samples from the same benchmarks, and **Cross Dataset** denotes Reasoning-Bypass Shortcut samples from MathVista.

Model	Ours				Held-Out				Cross-Dataset			
	$\overline{\Delta}^{\mathcal{C}}_{\text{conf}}$	$\overline{\Delta}^{\mathcal{C}}_{\text{RBS}}$	FR_1	FR_0	$\overline{\Delta}^{\mathcal{C}}_{\text{conf}}$	$\overline{\Delta}^{\mathcal{C}}_{\text{RBS}}$	FR_1	FR_0	$\overline{\Delta}^{\mathcal{C}}_{\text{conf}}$	$\overline{\Delta}^{\mathcal{C}}_{\text{RBS}}$	FR_1	FR_0
`Ocean-R1`	2.439	6.363	34.3%	6.4%	2.608	6.478	40.0%	7.3%	2.476	9.980	43.0%	4.0%
`ORSTA`	1.987	1.856	16.9%	1.2%	2.123	1.642	14.7%	3.0%	0.878	2.096	17.7%	4.2%
`Vlaa-Thinker`	1.803	2.403	23.2%	3.7%	1.000	2.242	27.0%	5.9%	2.838	1.925	17.3%	3.0%

Key Takeaway 3. As shown in Table 3, consistently positive effects on both **Held-Out** and **Cross-Dataset** settings indicate that the identified *System-1-like* representations generalize beyond the samples and datasets used for discovery.

Table 4: Negative controls for the selected causal interventions. **Ours** applies the selected intervention tuples $\mathcal{C}$ defined in Eq. 15, while **Gaussian Noise** and **Random-K** perturb the intervention operator and attention head selection, respectively.

Model	Ours				Gaussian Noise				Random-K			
	$\overline{\Delta}^{\mathcal{C}}_{\text{conf}}$	$\overline{\Delta}^{\mathcal{C}}_{\text{RBS}}$	FR_1	FR_0	$\overline{\Delta}^{\mathcal{C}}_{\text{conf}}$	$\overline{\Delta}^{\mathcal{C}}_{\text{RBS}}$	FR_1	FR_0	$\overline{\Delta}^{\mathcal{C}}_{\text{conf}}$	$\overline{\Delta}^{\mathcal{C}}_{\text{RBS}}$	FR_1	FR_0
`Ocean-R1`	2.439	6.363	34.3%	6.4%	0.201	1.145	11.7%	8.8%	-0.498	0.669	2.6%	3.1%
`ORSTA`	1.987	1.856	16.9%	1.2%	-0.176	0.681	4.6%	1.5%	-0.385	1.212	3.0%	4.9%
`Vlaa-Thinker`	1.803	2.403	23.2%	3.7%	0.106	0.216	5.1%	1.3%	-0.543	-0.113	4.4%	3.6%

Key Takeaway 4. As shown in Table 4, **Gaussian Noise** and **Random-K** produce mixed-sign effects across the two metrics, whereas **Ours** remains consistently positive on both. This contrast supports the specificity and effectiveness of the identified representations and intervention design.

Furthermore, we visualize how the joint intervention reshapes the output behavior associated with Reasoning-Bypass Shortcut. Specifically, we examine the sample wise distributions of $\Delta^{\mathcal{C}}_{\text{conf},i}$ and $\Delta^{\mathcal{C}}_{\text{RBS},i}$, which characterize the intervention effects on normal sample confidence and Reasoning-Bypass Shortcut suppression, respectively, as shown in Fig. 3.

As shown in Fig. 3, the joint intervention induces a clear shift in the output logit distribution, with samples moving substantially toward larger $\Delta^{\mathcal{C}}_{\text{RBS},i}$. The horizontal line at $\Delta^{\mathcal{C}}_{\text{RBS},i} = 0$ serves as a *zero-effect boundary*: samples above this boundary exhibit a positive shift from pre toward mid, indicating that Reasoning-Bypass Shortcut is suppressed at the output level. The pronounced upward shift after intervention further supports the causal role of the identified representations in driving Reasoning-Bypass Shortcut.

Finally, we analyze the impact of Reasoning-Bypass Shortcut on model accuracy, as shown in Appendix C.1. We find that, in many Reasoning-Bypass Shortcut cases, the final prediction is more accurate than the conclusion reached through explicit reasoning, indicating that reverting to the direct prediction can sometimes correct an unreliable reasoning trajectory. This suggests that reasoning

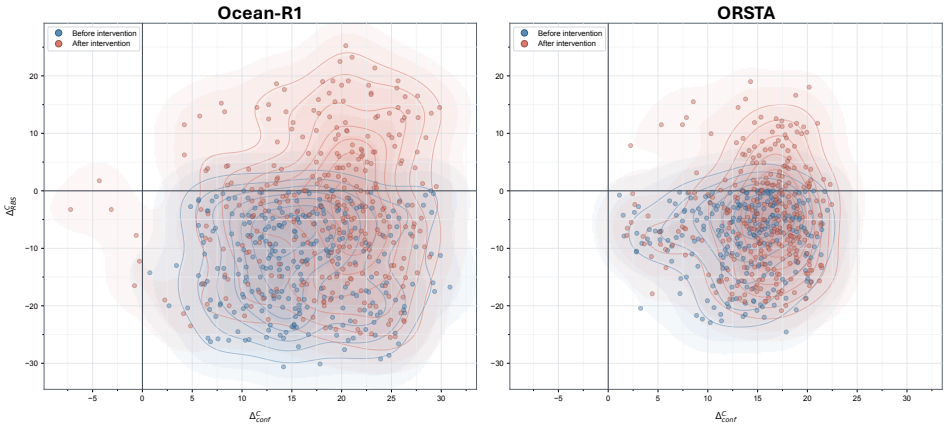

Figure 3: **Output distribution shift induced by joint intervention.** After intervention, the distribution shifts substantially toward $\Delta^{\mathcal{C}}_{\mathrm{RBS},i} > 0$, indicating suppression of Reasoning-Bypass Shortcut.

should not be treated as uniformly beneficial. Our key insight is that ***models should learn not only how to reason, but also when not to reason***.

4 Related Work

Multimodal Large Reasoning Models (MLRMs). Recent MLRMs extend chain-of-thought reasoning to multimodal problems through supervised fine-tuning, long-chain reasoning supervision, reflection, and visually grounded reasoning (Yao et al., 2024; Thawakar et al., 2025; Zhan et al., 2026; Wu et al., 2026). Post-training increasingly combines reasoning initialization with reinforcement learning, while RFT and GRPO directly strengthen reasoning and perception using verifiable multimodal rewards (Zhang et al., 2025b; Liu et al., 2025a; Huang et al., 2026; Wang et al., 2026b). Accordingly, recent work has moved from two-stage SFT+RL pipelines toward reinforcement learning at scale and more unified perception and reasoning frameworks (Yang et al., 2025a; Tan et al., 2025; Wang et al., 2025b; Liu et al., 2026b). However, improved task accuracy does not establish that the explicit reasoning trajectory actually governs the final prediction, leaving the interaction between deliberative reasoning and answer generation underexplored.

Process–Outcome Inconsistency in MLRMs. Recent studies show that an MLRM's reasoning trace and final answer need not agree; related failures are described as hallucination, unfaithful reasoning, or, under goal-directed misrepresentation, deception (Bai et al., 2024; Huang et al., 2025; Liu et al., 2025b; Fang et al., 2025). Mechanistic analyses suggest that models may encode visual evidence yet under-utilize it, while MLRMs exhibit perception–reasoning dissociation and accuracy–faithfulness trade-offs (Liu et al., 2026c; Lv et al., 2026; Zhao et al., 2026). Correspondingly, mitigation has progressed from decoding, and verification toward evidence calibration and consistency-constrained RL (Leng et al., 2024; Wang et al., 2024; Lv et al., 2026; Kancheti et al., 2026). Nevertheless, these studies diagnose evidence under-utilization or regularize consistency, rather than explain why a reasoning trajectory can be discarded at the answering stage, motivating our study of the pathway that redirects prediction toward direct answering.

5 Conclusion

In this work, we identify and investigate Reasoning-Bypass Shortcut, a prevalent form of reasoning inconsistency in which MLRMs abandon their *System-2-like* reasoning conclusions and revert to *System-1-like* direct predictions. We introduce **DiffProbe** to localize the internal representations associated with this behavior, and further use causal activation interventions to isolate representations that actively influence Reasoning-Bypass Shortcut. Joint interventions consistently suppress Reasoning-Bypass Shortcut across held out samples and cross dataset evaluations, while negative controls validate the specificity of the identified representations and operators. These findings provide a representation level perspective for understanding reasoning inconsistency and offer a foundation for studying seemingly distinct failure behaviors through their shared internal mechanisms.

AI USE STATEMENT

In this work, we used generative AI tools for assist with translation. We have not used generative AI tools for other tasks with required disclosure, and the rest of the required disclosure tasks are not applicable to this work. Additionally, we used generative AI tools for identify relevant literature. We have reviewed all AI-assisted work. We carefully reviewed the translated content sentence by sentence to ensure that it did not deviate from our original meaning or go beyond the scope of the information we provided. We also verified the relevant literature suggested by the LLM by searching academic websites such as Google Scholar to ensure that the cited works were authentic and valid. We take responsibility for the final content of this work, including text, claims or artifacts produced with the aid of generative AI.

REPRODUCIBILITY STATEMENT

We provide an anonymous code repository and the complete set of generated outputs. The experimental setup—datasets, models, and evaluation protocols—is summarized in Section 2 and detailed in Appendix B, with links to openly available sources. The exact configurations required to reproduce results, including prompt templates, decoding parameters and extractor details, are specified in Appendix B.2 and Appendix B.3. All third-party datasets and checkpoints used in our work are publicly available. These materials collectively enable end-to-end reproduction of our findings.

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A NOTATIONS

The notation used in this paper is summarized in Table 5.

Table 5: **Key notations used throughout our formulation and analysis.**

Notation	Description
$\mathcal{R}$, $\mathbf{X}_s$, $\mathbf{X}_v$, $\mathbf{X}_q$	Multimodal reasoning model; system prompt, visual input, and question input
$\mathbf{X} = [\mathbf{X}_s, \mathbf{X}_v, \mathbf{X}_q]$	Complete multimodal input to $\mathcal{R}$
$\mathbf{r}$, y	Explicit reasoning trace and final answer generated by $\mathcal{R}$
$\mathrm{Ext}(\cdot)$	Extractor that obtains the predicted answer from generated text
y'_t, $\mathbf{r}_{<t}$, T	Answer elicited after reasoning prefix $\mathbf{r}_{<t}$; T denotes the complete reasoning length
pre, **mid**, **post**	Prediction before reasoning, conclusion extracted from reasoning, and final prediction after reasoning
z_i, $\mathcal{D}_0$, $\mathcal{D}_1$	Behavioral label of sample i; normal samples ($z_i = 0$) and Reasoning-Bypass Shortcut samples ($z_i = 1$)
$\mathbf{h}_{i,t}^{(\ell,h)}$	Representation of attention head h in layer ℓ for sample i at reasoning stage t
$\mathbf{h}_{i,\mathrm{pre}}^{(\ell,h)}$, $\mathbf{h}_{i,\mathrm{post}}^{(\ell,h)}$	Attention head representations at the pre-thinking and post-thinking decision points
$\Delta\mathbf{h}_i^{(\ell,h)}$	Reasoning differential representation, $\mathbf{h}_{i,\mathrm{post}}^{(\ell,h)} - \mathbf{h}_{i,\mathrm{pre}}^{(\ell,h)}$
$\boldsymbol{\theta}^{(\ell,h)}$, $b^{(\ell,h)}$, $p_i^{(\ell,h)}$	Parameters and predicted probability of the DiffProbe for attention head (ℓ, h)
$\mathcal{I}_m$, m	Activation intervention operator and its type, $m \in \{\mathrm{Zero}, \mathrm{Neg}, \mathrm{Patch}\}$
$c = (\ell, h, m)$, $\mathcal{C}$	Individual intervention tuple and the selected set of causal intervention tuples
$\mathbf{g}_i$, $\widetilde{\mathbf{g}}_i^c$	Output logits before and after applying intervention c
$\Delta_{\mathrm{conf},i}^c$, $\Delta_{\mathrm{RBS},i}^c$	Intervention effects on normal-sample confidence and Reasoning-Bypass Shortcut suppression for sample i
$\overline{\Delta}_{\mathrm{conf}}^c$, $\overline{\Delta}_{\mathrm{RBS}}^c$	Average effects of an individual intervention tuple c over $\mathcal{D}_0$ and $\mathcal{D}_1$
$\overline{\Delta}_{\mathrm{conf}}^{\mathcal{C}}$, $\overline{\Delta}_{\mathrm{RBS}}^{\mathcal{C}}$	Average effects after jointly applying all selected intervention tuples in $\mathcal{C}$
FR_0, FR_1	Answer flip rates on normal samples and Reasoning-Bypass Shortcut samples, respectively
RI%, RBS/RI%	Reasoning inconsistency rate and proportion of Reasoning-Bypass Shortcut among reasoning-inconsistent cases

B EXPERIMENT DETAILS

B.1 BASELINES

Models. We evaluate Reasoning-Bypass Shortcut on seven recent open-weight MLRMs at the 7B scale. (i) MM-Eureka(Meng et al., 2025) extends large scale rule-based reinforcement learning to multimodal reasoning and trains Qwen2.5-VL with verifiable rewards. (ii) **Ocean-R1** (Ming et al., 2025) adopts a two-stage rule-based RL framework that first strengthens reasoning and subsequently improves visual perception. (iii) **Orsta** (Ma et al., 2025) is trained with the V-Triune framework, which jointly optimizes visual reasoning and perception tasks within a unified RL pipeline. (iv) **R1-Onevision** (Yang et al., 2025b) introduces cross-modal formalization to convert visual information into structured representations and is post-trained with SFT followed by RL. (v) **GThinker** (Zhan et al., 2026) introduces Cue-Rethinking and a two-stage training framework to encourage iterative reconsideration of visual cues during reasoning. (vi) **Spatial-SSRL** (Liu et al., 2026a) improves spatial reasoning through self-supervised reinforcement learning with intrinsically verifiable visual pretext tasks. (vii) **VLAA-Thinker** (Chen et al., 2025) is trained with reinforcement learning using mixed perception and cognition rewards to promote adaptive multimodal reasoning. For the internal representation analysis, we focus on Ocean-R1, Orsta, and VLAA-Thinker, which exhibit the highest prevalence of Reasoning-Bypass Shortcut in our characterization.

Datasets. We evaluate Reasoning-Bypass Shortcut on four benchmarks spanning capabilities from general visual perception to complex reasoning. **VMCBench** (Zhang et al., 2025c) converts 20 existing VQA datasets into a unified multiple-choice benchmark containing 9,018 questions across general understanding, reasoning, OCR, and document and chart understanding. **MathVista** (Lu et al., 2023) contains 6,141 examples collected from 31 datasets and evaluates mathematical reasoning in diverse visual contexts. **SEED-Bench** (Li et al., 2024a) consists of approximately 19K human-annotated multiple-choice questions covering 12 dimensions of multimodal comprehension. **MMT-Bench** (Ying et al., 2024) contains 31,325 multiple-choice questions across 32 meta-tasks and 162 subtasks, covering visual recognition, localization, reasoning, and planning. We use VMCBench, SEED-Bench, and MMT-Bench for DiffProbe and causal intervention discovery, while MathVista is additionally used for cross-dataset evaluation.

License. All evaluated models are publicly available checkpoints. `R1-Onevision` and `MM-Eureka` are released under the Apache-2.0 license, while `Orsta` is released under the MIT license. The released `GThinker` and `VLAA-Thinker` checkpoints are licensed under CC BY-NC 4.0. The `Spatial-SSRL` model metadata lists Apache-2.0, while its project documentation additionally specifies research-use conditions for the released resources. `Ocean-R1` is publicly released through its official GitHub and Hugging Face repositories, but we did not identify an explicit license statement for its model weights. We use all models solely for academic evaluation and do not redistribute their weights.

B.2 Evaluation Setup Details

Prompt Template. For all multiple choice questions, we use the following prompt template:

> You FIRST think about the reasoning process as an internal monologue and then provide the final answer. The reasoning process MUST BE enclosed within <think></think> tags. The final answer must be an option letter from the given choices, enclosed in <answer></answer> tags. Let's think more.
> {question}

Evaluation. During evaluation, we parse the model output using a regular expression to extract the option letter enclosed in `<answer>...</answer>` and compare it with the ground truth answer.

Generation Configuration. We use the same decoding settings across all models and datasets.

Parameter	Value
`max_new_tokens`	1024
`do_sample`	False

B.3 Extractor Details

We use different extraction strategies for pre, mid, and post. For pre and post, the model is explicitly required to place its final prediction inside `<answer></answer>` tags. We therefore use regular expressions to extract the option letter enclosed by these tags.

For mid, the reasoning trace is generally free form and may contain multiple intermediate hypotheses or references to different options. We therefore use an LLM based extractor to identify the latest committed conclusion expressed in the reasoning segment. The extractor is prompted as follows:

> You are an answer extractor for multiple-choice QA.
> Task: Given a question with options and a MID reasoning segment, infer which option the MID segment commits to. Return ONLY one uppercase letter: A or B or C or D.
> Guidelines:
> 1) IMPORTANT: This input is MID-only text. Do NOT assume or hallucinate any final answer outside this segment.
> 2) Reasoning may be noisy, long, or messy. Focus on the latest committed conclusion in this MID segment.
> 3) Do NOT treat mere rehearsal or listing of the four choices as the answer (e.g., repeating "Option A ... B ... C ... D", or walking through each option letter without a final pick). Those letters are not the model's committed choice.
> 4) Prefer explicit commitment signals, often near the end of the segment: "answer is X", "I choose X", "final answer X", "therefore X", "thus option X", "boxed{X}".
> 5) If the text outputs option content or value instead of a letter, map the content or value back to A/B/C/D using the options.
> 6) If multiple commitment cues appear, use the last one that clearly states the chosen option, rather than the first option letter appearing in an enumeration.
> 7) The letter may appear in lowercase or with punctuation, e.g., "a)", "[b]", "option c", or "d)".

8) If no committed option can be found, output nothing and do not guess.

Output format:
Exactly one character from {A,B,C,D}.
Question and Options:
{question}
Reasoning text:
{think_content}

This extractor is used only to map the reasoning segment to its committed option and does not access the model's final answer. To ensure the stability and reliability of the extracted labels, we independently perform the extraction using GPT-5.5 and Qwen3.6-Max-Preview (Qwen Team, 2026). For each sample, each model performs the extraction three times, yielding six independent extraction results in total. We compare the resulting labels across models and repeated runs to verify their consistency.

C Detailed Experimental Results

C.1 Accuracy Impact of Reasoning-Bypass Shortcuts

The results in Table 6 reveal a consistent accuracy advantage of the final prediction over the explicit reasoning conclusion on Reasoning-Bypass Shortcut cases. At the aggregate level, replacing post with mid decreases accuracy for every evaluated model, with drops ranging from 13.85 percentage points for MM-Eureka to 43.81 percentage points for GThinker. The same trend holds across individual benchmarks. For example, on SEED-Bench, GThinker drops from 67.77% to 21.25%, while Vlaa-Thinker drops from 64.05% to 22.97%. Since post = pre by definition in Reasoning-Bypass Shortcut, these results indicate that the model's direct *System-1-like* prediction is substantially more accurate than the conclusion produced by explicit *System-2-like* reasoning in many shortcut cases.

This finding suggests that the competition between System-1-like and System-2-like pathways should not be viewed as purely pathological. On the one hand, Reasoning-Bypass Shortcut exposes a clear failure of reasoning consistency, because the final answer disregards the conclusion established by the explicit reasoning process. On the other hand, this bypass can improve task accuracy when the reasoning trajectory itself is unreliable. More broadly, this points to a limitation of reasoning architectures that treat more explicit reasoning as uniformly beneficial. A capable reasoning model may need to learn not only ***how to reason***, but also ***when reasoning should be trusted and when it should be bypassed***.

C.2 Statistical Analysis

C.2.1 Answer-Letter Distribution in Reasoning-Bypass Shortcut Cases

Figure 4 and Table 7 further reveal that the transition from mid to post is accompanied by a substantial redistribution of answer preferences. Notably, the dominant answer at the reasoning stage differs from that at the final answering stage for all seven models. For Ocean-R1 and ORSTA, the dominant answer shifts from A at mid (36.39% and 30.07%) to D at post (30.05% and 33.20%). Similar transitions appear in Vlaa-Thinker, from C (27.99%) to D (32.28%), and in Spatial-SSRL, from B (32.93%) to D (43.78%). The redistribution is particularly pronounced for MM-Eureka, where A increases from only 12.77% at mid to 51.06% at post, while B decreases from 35.46% to 16.31%. R1-OneVision similarly shifts from a C-dominant reasoning distribution (35.39%) to an A-dominant final distribution (37.08%), whereas GThinker shifts from A (39.69%) to D (33.55%). These changes are also visually apparent in Fig. 4, where the mid and post distributions exhibit clear model-specific separations rather than small local fluctuations. :chatgpt-content-referenceindex="0"

More broadly, these results suggest that Reasoning-Bypass Shortcut is not simply a case in which the final answer randomly disagrees with the reasoning conclusion. Instead, the answering stage systematically reorganizes the model's output preference, often toward a different dominant answer

Table 6: Accuracy on RBS cases before and after replacing post with mid. $\Delta\mathrm{Acc} = \mathrm{Acc}_{\mathrm{mid}} - \mathrm{Acc}_{\mathrm{post}}$.

Dataset	Post Acc.	Mid Acc.	ΔAcc. (pp)
Ocean-R1			
VMCBench	–	–	–
SEED-Bench	50.25%	32.62%	-17.63
MMT-Bench	48.20%	29.28%	-18.92
All evaluable	**49.93%**	**32.10%**	**-17.83**
ORSTA			
VMCBench	–	–	–
SEED-Bench	60.37%	25.20%	-35.16
MMT-Bench	47.10%	33.55%	-13.55
All evaluable	**57.19%**	**27.20%**	**-29.98**
Vlaa-Thinker			
VMCBench	–	–	–
SEED-Bench	64.05%	22.97%	-41.08
MMT-Bench	53.62%	18.84%	-34.78
All evaluable	**62.41%**	**22.32%**	**-40.09**
MM-Eureka			
VMCBench	–	–	–
SEED-Bench	47.22%	38.89%	-8.33
MMT-Bench	41.38%	20.69%	-20.69
All evaluable	**44.62%**	**30.77%**	**-13.85**
R1-OneVision			
VMCBench	–	–	–
SEED-Bench	53.85%	31.62%	-22.22
MMT-Bench	57.14%	14.29%	-42.86
All evaluable	**54.20%**	**29.77%**	**-24.43**
GThinker			
VMCBench	–	–	–
SEED-Bench	67.77%	21.25%	-46.52
MMT-Bench	56.90%	25.86%	-31.03
All evaluable	**65.86%**	**22.05%**	**-43.81**
Spatial-SSRL			
VMCBench	–	–	–
SEED-Bench	57.77%	27.57%	-30.21
MMT-Bench	39.08%	28.74%	-10.34
All evaluable	**53.97%**	**27.80%**	**-26.17**

pattern. Across the seven models, the reasoning-stage distributions are relatively diverse, whereas the post distributions are frequently concentrated on D or A. Since Reasoning-Bypass Shortcut specifically satisfies $\mathrm{pre} = \mathrm{post} \neq \mathrm{mid}$, this redistribution is consistent with the final decision returning toward the model's direct-answering preference rather than preserving the conclusion established through explicit reasoning. At the same time, these answer-letter statistics should be interpreted as behavioral evidence rather than as proof of a universal positional bias, since they are conditioned on RBS cases and pooled across benchmarks. Nevertheless, the consistent separation between mid and post across models provides additional evidence that Reasoning-Bypass Shortcut reflects a structured transition between two competing decision regimes rather than incidental output inconsistency.

C.2.2 Evolution of Answer Preferences During Reasoning

To further characterize how the model's decision evolves throughout reasoning, we sample 100 examples from Ocean-R1 and ORSTA and evaluate the conditional answer preference defined in

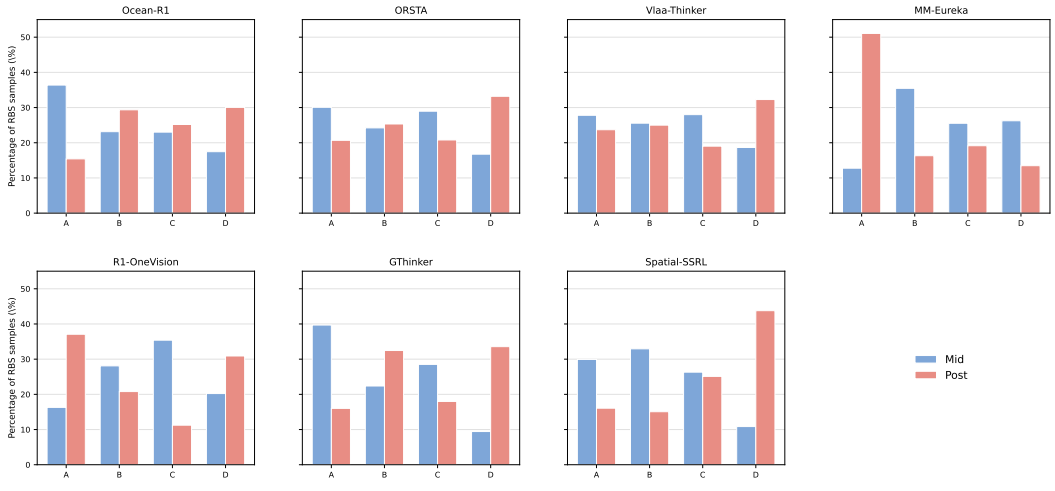

Figure 4: Mid and post answer-letter distributions over all RBS (label-1) samples, pooled across the four benchmarks for each model. Percentages within each stage sum to 100%.

Table 7: A/B/C/D percentages for mid and post answers on all RBS samples.

	Mid (%)				Post (%)				
Model	A	B	C	D	A	B	C	D	N
Ocean-R1	36.39	23.14	23.01	17.46	15.41	29.35	25.18	30.05	2303
ORSTA	30.07	24.22	28.96	16.75	20.69	25.33	20.79	33.20	991
Vlaa-Thinker	27.80	25.56	27.99	18.66	23.69	25.00	19.03	32.28	536
MM-Eureka	12.77	35.46	25.53	26.24	51.06	16.31	19.15	13.48	141
R1-OneVision	16.29	28.09	35.39	20.22	37.08	20.79	11.24	30.90	178
GThinker	39.69	22.37	28.51	9.43	16.01	32.46	17.98	33.55	456
Spatial-SSRL	29.92	32.93	26.31	10.84	16.06	15.06	25.10	43.78	498

Eq. 3. Specifically, for each sample with reasoning length T, we progressively reveal the reasoning trace at 2% intervals, i.e.,

$$t_j = \lfloor 0.02jT \rfloor, \qquad j = 1, \ldots, 50,$$

and compute the corresponding prediction y'_{t_j}. This yields a 100×50 decision trajectory for each model, where each row denotes one sample and each column denotes one reasoning stage. As shown in Fig. 5, the model's answer preference is often piecewise stable but undergoes abrupt transitions as reasoning proceeds, with some samples exhibiting multiple switches or late-stage reversals. This indicates that the final prediction is not simply a monotonic refinement of the reasoning process; instead, competing answer preferences can emerge and overwrite one another throughout reasoning, providing behavioral evidence for the pathway competition underlying Reasoning-Bypass Shortcut.

C.3 Head-by-head Results

Quadrant based characterization. To characterize the causal role of individual attention heads, we organize all single head interventions according to their effects on normal samples and Reasoning-Bypass Shortcut samples. For each model and dataset pair, we take the top 20 attention heads identified by DiffProbe and independently apply three intervention operators, **Zero**, **Neg**, and **Patch**. This results in $20 \times 3 = 60$ intervention tuples for each model and dataset pair and 540 tuples in total across the three models and three datasets.

For an intervention tuple $c = (\ell, h, m)$, the horizontal coordinate in Fig. 6 is Δ^c_{conf}, which measures the change in predictive confidence on normal samples. A positive value indicates that the intervention reduces predictive entropy and increases confidence, whereas a negative value indicates decreased confidence. The vertical coordinate is Δ^c_{RBS}, which measures the change in the logit margin between mid and pre on Reasoning-Bypass Shortcut samples. A positive value indicates a shift from pre

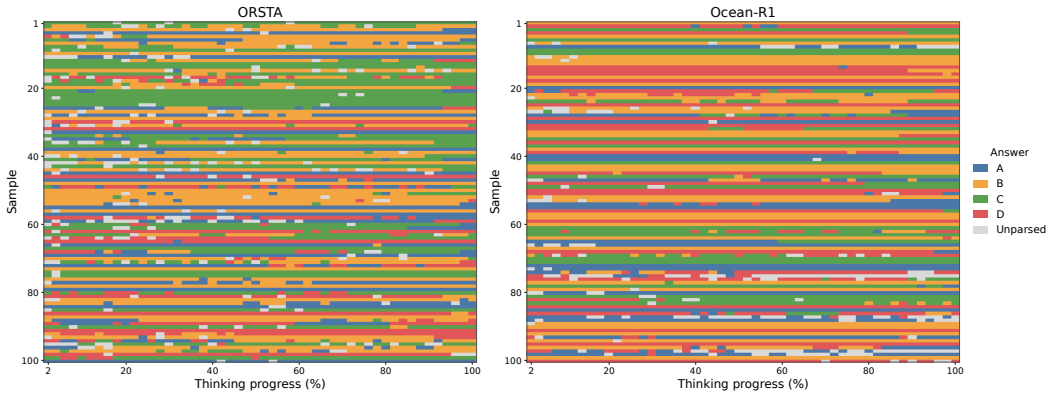

Figure 5: Evolution of answer preferences throughout reasoning for ORSTA and Ocean-R1. Each row represents one sample, and each column corresponds to a 2% reasoning interval. Colors denote the conditional prediction y'_t at each reasoning stage.

Table 8: Distribution of Q1 intervention tuples across different operators. Q1 denotes interventions that simultaneously increase confidence on normal samples and suppress Reasoning-Bypass Shortcut.

Operator	Q1 Count	Share of Q1
Zero	36	37.5%
Neg	21	21.9%
Patch	39	40.6%
Total	**96**	**100.0%**

toward mid and therefore suppression of Reasoning-Bypass Shortcut, whereas a negative value indicates a shift toward pre and therefore enhancement of Reasoning-Bypass Shortcut. The zero lines of the two effects naturally divide the intervention tuples into four quadrants.

The four quadrants admit distinct causal interpretations. In **Q1** ($\Delta^c_{\mathrm{conf}} > 0$ and $\Delta^c_{\mathrm{RBS}} > 0$), the intervention increases confidence on normal samples while simultaneously shifting Reasoning-Bypass Shortcut samples from pre toward mid. These tuples therefore suppress Reasoning-Bypass Shortcut without degrading normal behavior and provide the clearest evidence of a causal pathway associated with the shortcut. In contrast, **Q3** ($\Delta^c_{\mathrm{conf}} < 0$ and $\Delta^c_{\mathrm{RBS}} < 0$) exhibits the opposite direction: the intervention decreases confidence on normal samples and further shifts Reasoning-Bypass Shortcut samples toward pre. Q3 therefore captures interventions that enhance Reasoning-Bypass Shortcut, providing complementary evidence for the opposite causal direction.

By comparison, **Q2** and **Q4** are more consistent with generic confidence modulation. In Q2, the intervention decreases normal sample confidence while producing an apparent shift from pre toward mid on Reasoning-Bypass Shortcut samples. Such a pattern can arise simply because weakening the currently dominant prediction also weakens pre in shortcut cases. Conversely, Q4 increases normal sample confidence while further favoring pre over mid, which is consistent with globally strengthening the currently dominant prediction. Therefore, an opposite sign between Δ^c_{conf} and Δ^c_{RBS} does not provide sufficient evidence for a Reasoning-Bypass Shortcut specific causal effect. This motivates our use of the same sign criterion to distinguish Reasoning-Bypass Shortcut related interventions from generic changes in model confidence.

Among the 540 single head intervention settings, 96 (17.8%) fall into Q1, showing that only a relatively sparse subset of the DiffProbe localized representations admits an intervention that simultaneously preserves normal behavior and suppresses Reasoning-Bypass Shortcut. Patch contributes the largest number of Q1 tuples (39), followed by Zero (36) and Neg (21). This sparsity also indicates that a high DiffProbe score alone does not imply a causal role in Reasoning-Bypass Shortcut: probing provides candidate localization, while intervention is necessary to further distinguish causal representations and their functional directions.

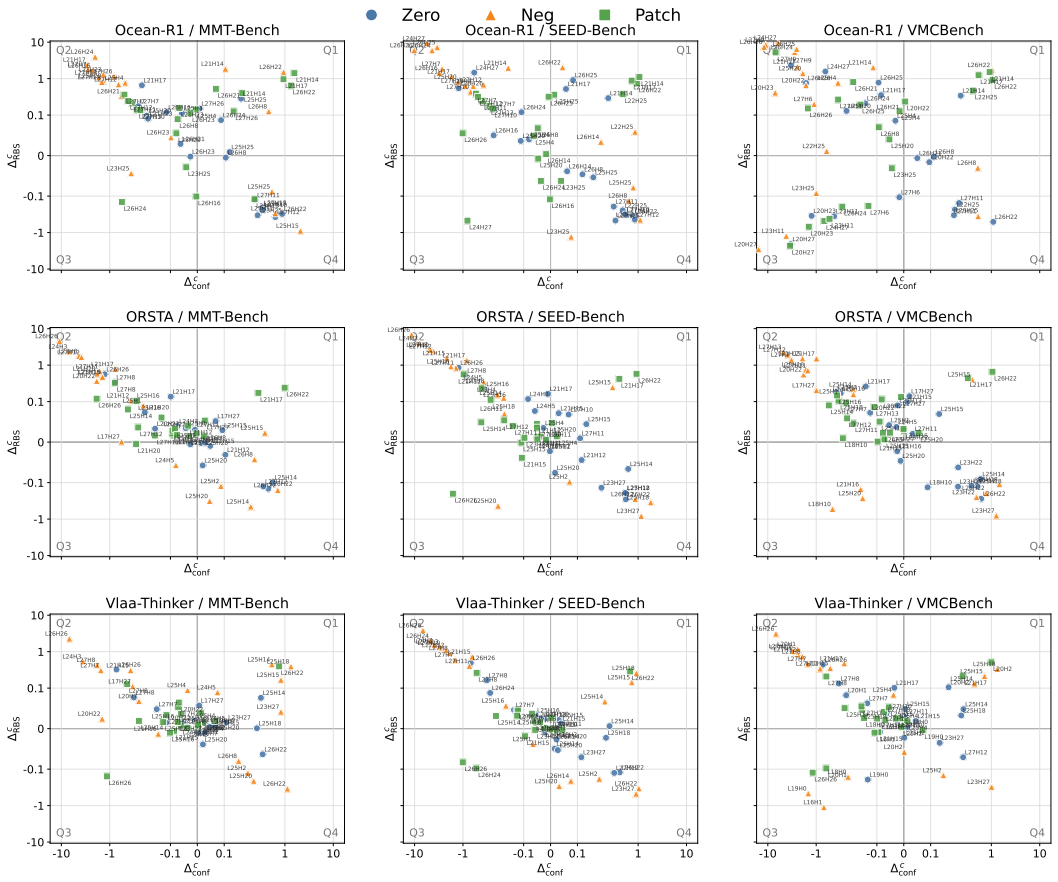

Figure 6: Single head intervention effects across all model and dataset pairs. Each point represents one attention head under one intervention operator. The horizontal axis denotes Δ^c_{conf} on normal samples, while the vertical axis denotes Δ^c_{RBS} on Reasoning-Bypass Shortcut samples. Q1 and Q3 capture Reasoning-Bypass Shortcut specific causal directions, whereas Q2 and Q4 are more consistent with generic confidence modulation. Coordinates are shown on shared symmetric log axes.

Table 9: Representative intervention tuples that consistently fall into Q1 across all three evaluation datasets. Values are averaged over MMT-Bench, SEED-Bench, and VMCBench.

Model	Operator	Head	Q1 Datasets	$\overline{\Delta}_{\text{conf}}$	$\overline{\Delta}_{\text{RBS}}$
Ocean-R1	Patch	L21H14	3/3	1.185	1.345
Ocean-R1	Neg	L26H22	3/3	0.670	1.765
ORSTA	Patch	L26H22	3/3	0.989	0.492
Vlaa-Thinker	Neg	L25H18	3/3	1.194	0.330

The head level results reveal several additional patterns. First, the causal effects are not uniformly distributed among the representations identified by DiffProbe. Instead, a small number of intervention tuples remain in Q1 across all three datasets. For example, Patch on Ocean-R1 L21H14 yields positive effects on both axes for MMT-Bench, SEED-Bench, and VMCBench, with average effects of 1.185 on normal sample confidence and 1.345 on Reasoning-Bypass Shortcut suppression. Similarly, ORSTA L26H22 under Patch and Vlaa-Thinker L25H18 under Neg consistently remain in Q1 across all three datasets. Such cross dataset consistency suggests that these effects are not tied to a particular benchmark distribution.

Second, the results highlight the importance of considering the attention head and intervention operator jointly. The causal unit in our analysis is therefore the tuple $c = (\ell, h, m)$ rather than the

Table 10: Representative single head intervention effects from the four quadrants in Fig. 6. Q1 and Q3 correspond to interventions that suppress and enhance Reasoning-Bypass Shortcut, respectively, whereas Q2 and Q4 exhibit opposite effects on normal sample confidence and Reasoning-Bypass Shortcut.

Model	Dataset	Operator	Head	Δ^{c}_{conf}	Δ^{c}_{RBS}	Quadrant
Q1: Reasoning-Bypass Shortcut Suppression						
Ocean-R1	MMT-Bench	Patch	L21H14	1.569	1.416	Q1
ORSTA	SEED-Bench	Neg	L25H15	0.297	0.248	Q1
Vlaa-Thinker	VMCBench	Patch	L20H2	1.003	0.511	Q1
Q2: Confidence Decrease						
Ocean-R1	VMCBench	Neg	L24H27	-6.067	9.796	Q2
ORSTA	SEED-Bench	Neg	L24H3	-7.915	4.001	Q2
Vlaa-Thinker	SEED-Bench	Neg	L26H26	-6.715	3.856	Q2
Q3: Reasoning-Bypass Shortcut Enhancement						
Ocean-R1	VMCBench	Zero	L20H27	-3.365	-2.066	Q3
ORSTA	SEED-Bench	Neg	L25H20	-0.195	-0.431	Q3
Vlaa-Thinker	VMCBench	Neg	L19H0	-1.456	-0.462	Q3
Q4: Confidence Increase						
Ocean-R1	MMT-Bench	Zero	L26H22	0.878	-0.309	Q4
ORSTA	SEED-Bench	Zero	L25H18	0.547	-0.193	Q4
Vlaa-Thinker	MMT-Bench	Neg	L26H22	1.126	-0.342	Q4

attention head alone. Nevertheless, several heads exhibit consistent behavior under more than one operator. For example, Ocean-R1 L21H14 remains in Q1 under both Zero and Patch across the evaluated datasets, while several heads in ORSTA and Vlaa-Thinker show similar consistency under multiple operators. This provides stronger evidence that the corresponding representations themselves are involved in Reasoning-Bypass Shortcut, rather than the observed effect being solely an artifact of a particular intervention operator.

Finally, the consistent tuples are concentrated in the later layers among the DiffProbe selected candidates, including L21, L25, and L26. We do not interpret this as evidence that Reasoning-Bypass Shortcut is exclusively localized to late layers, since the intervention candidates are already conditioned on DiffProbe selection. Rather, the result shows that within the representations localized by DiffProbe, a sparse subset of later layer attention heads exhibits particularly stable causal effects across datasets.

Table 10 provides representative examples from all four quadrants. The effects can differ substantially even among attention heads selected by DiffProbe. For example, intervening on Ocean-R1 L21H14 with Patch simultaneously increases normal sample confidence and shifts Reasoning-Bypass Shortcut samples toward mid, placing it in Q1. In contrast, Ocean-R1 L20H27 under Zero produces negative changes on both axes and therefore lies in Q3, indicating the opposite causal direction. The Q2 and Q4 examples further illustrate why the two effects must be considered jointly: large changes in Δ^{c}_{RBS} can accompany a general decrease or increase in model confidence and therefore do not necessarily indicate a Reasoning-Bypass Shortcut specific causal effect.

D Case Study

For each evaluated model, we present ten representative Reasoning-Bypass Shortcut cases, as shown in Figs. 7–13.

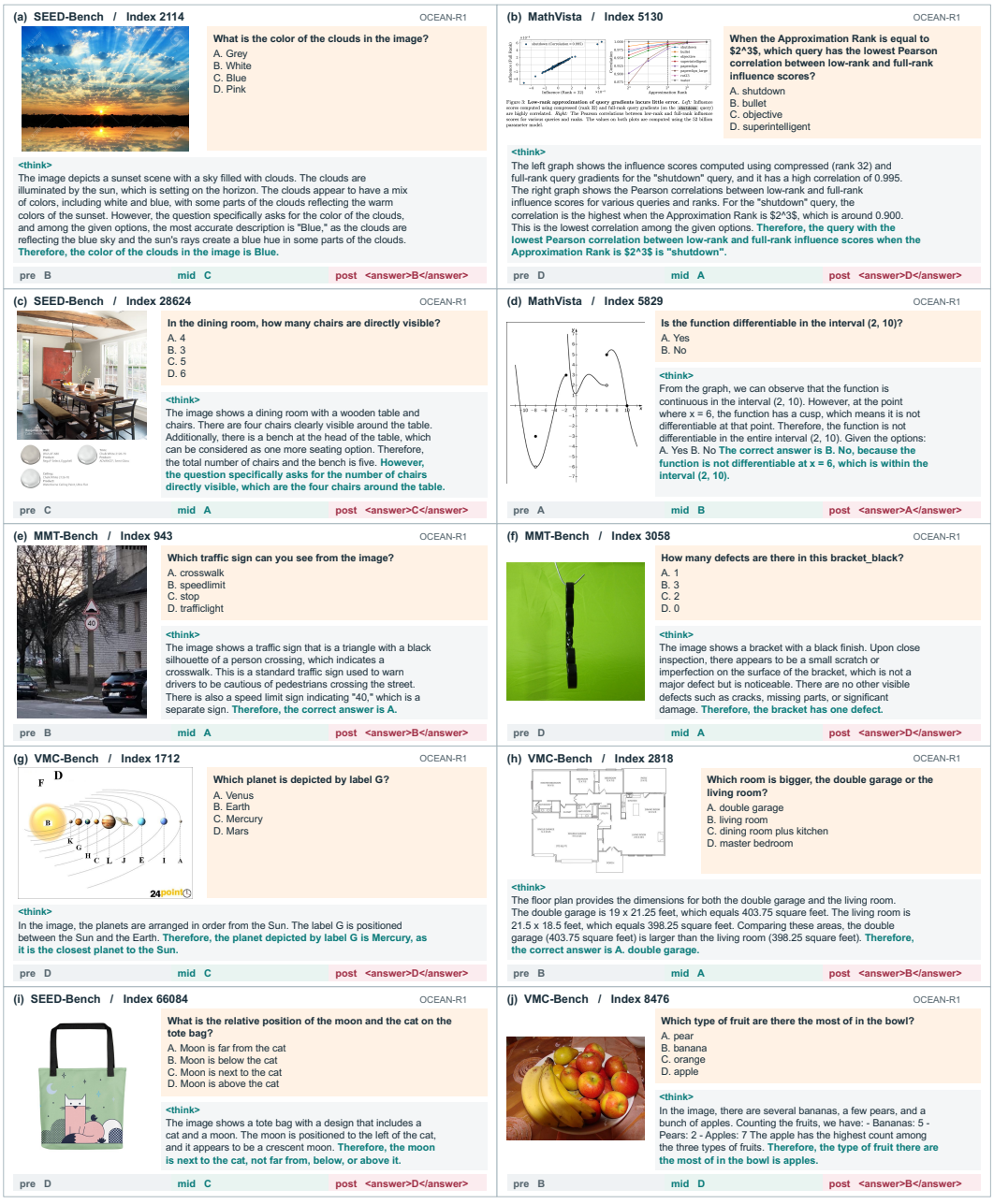

Figure 7: **Case study of Reasoning-Bypass Shortcut in Ocean-R1 across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit pre $=$ post $\neq$ mid.

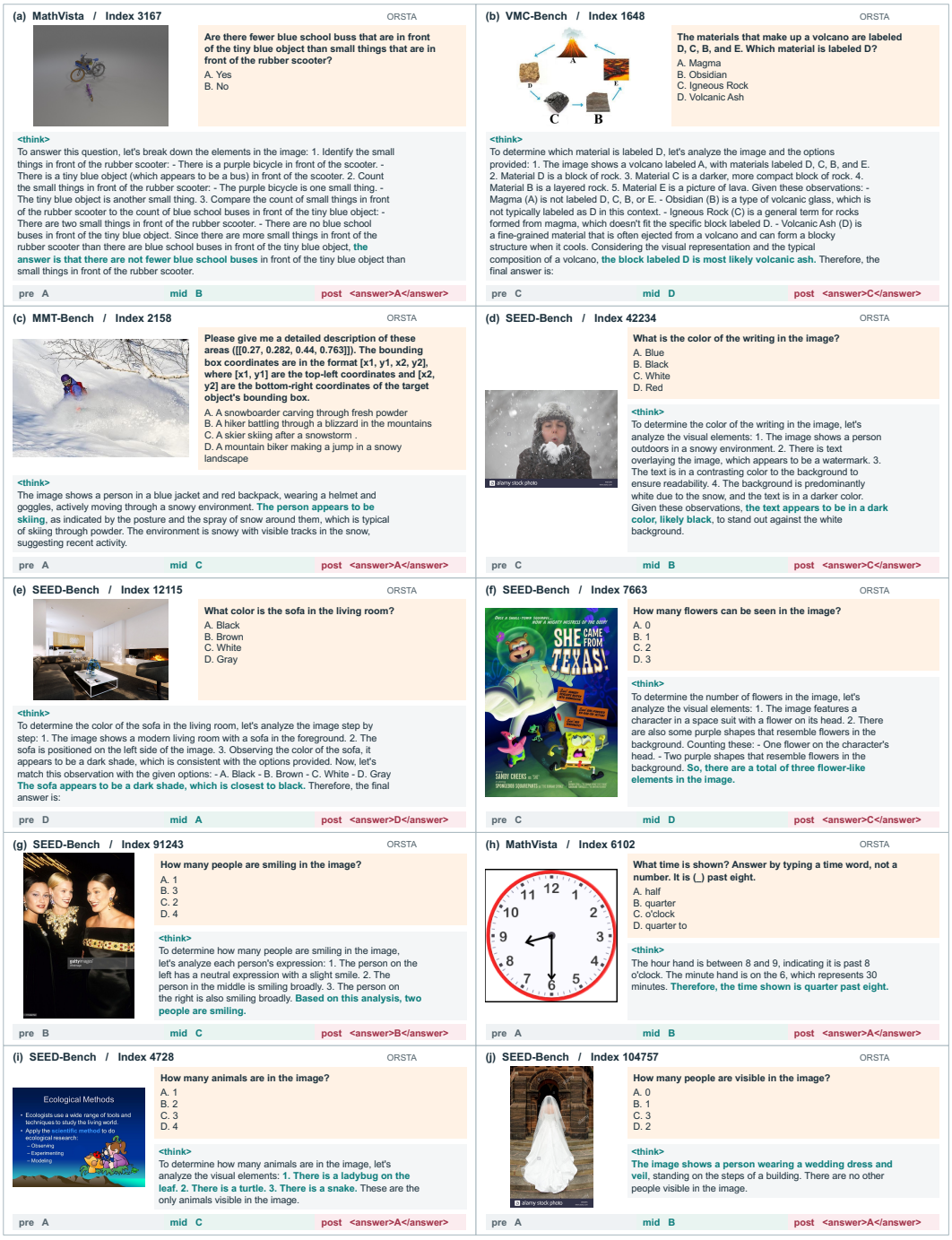

Figure 8: **Case study of Reasoning-Bypass Shortcut in ORSTA across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit $\text{pre} = \text{post} \neq \text{mid}$.



Figure 9: **Case study of Reasoning-Bypass Shortcut in MM-Eureka across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit $\text{pre} = \text{post} \neq \text{mid}$.



Figure 10: **Case study of Reasoning-Bypass Shortcut in R1-OneVision across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit $\text{pre} = \text{post} \neq \text{mid}$.



Figure 11: **Case study of Reasoning-Bypass Shortcut in GThinker across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit $\text{pre} = \text{post} \neq \text{mid}$.

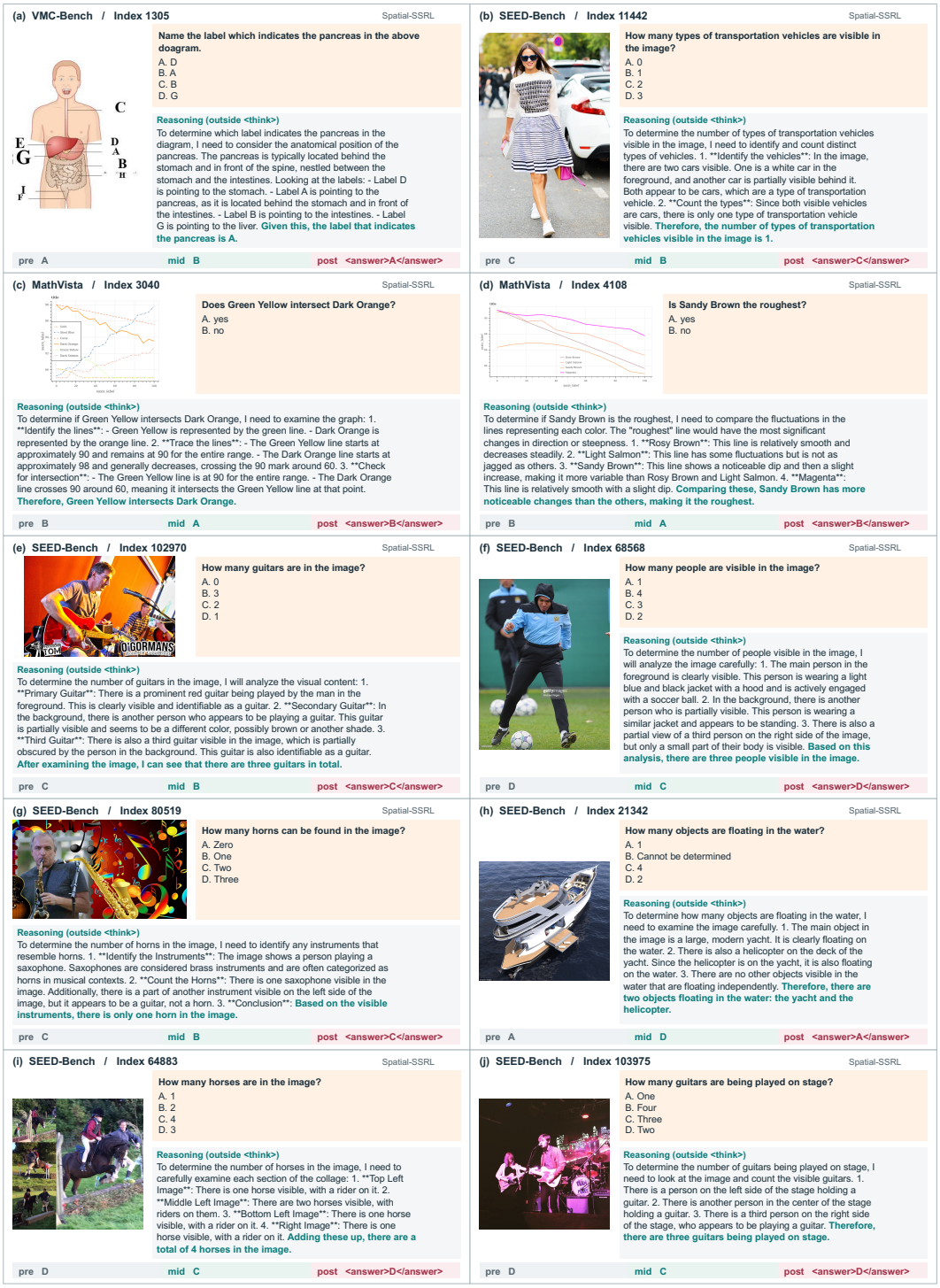

Figure 12: **Case study of Reasoning-Bypass Shortcut in Spatial-SSRL across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit $\text{pre} = \text{post} \neq \text{mid}$.



Figure 13: **Case study of Reasoning-Bypass Shortcut in Vlaa-Thinker across 10 representative examples.** Teal denotes the reasoning conclusion (**mid**), while Burgundy denotes the final answer (**post**). These cases consistently exhibit $\text{pre} = \text{post} \neq \text{mid}$.