# X-REASONER: TOWARDS GENERALIZABLE REASONING ACROSS MODALITIES AND DOMAINS

#### **Anonymous authors**

000

001

002003004

010 011

012

013

014

015

016

017

018

019

021

025

026

027

028

029

031

032

033

034

037

040

041

042

043

044

045

046

047

048

Paper under double-blind review

## **ABSTRACT**

Recent proprietary models (e.g., o3) have begun to demonstrate strong multimodal reasoning capabilities. Yet, most existing open-source research concentrates on training text-only reasoning models, with evaluations limited to mainly mathematical and general-domain tasks. Therefore, it remains unclear how to effectively extend reasoning capabilities beyond text input and general domains. This paper explores a fundamental research question: Is reasoning generalizable across modalities and domains? Our findings support an affirmative answer: Generaldomain text-based post-training can enable such strong generalizable reasoning, which is even more effective than in-domain multimodal training. Leveraging this finding, we introduce X-REASONER, a vision-language model with reasoning post training solely from general-domain text for generalizable reasoning, using a two-stage approach: an initial supervised fine-tuning phase with distilled long chain-of-thoughts, followed by reinforcement learning with verifiable rewards. Experiments show that X-REASONER successfully transfers reasoning capabilities to both multimodal and out-of-domain settings, outperforming prior models trained with in-domain and multimodal data across various general and medical benchmarks (Figure 1). Additionally, we find that X-REASONER's performance in specialized domains can be further enhanced through continued training on domain-specific text-only data. Building upon this, we introduce X-REASONER-MED, a medical-specialized variant that achieves SOTA (state-of-the-art)-level performance on numerous text-only and multimodal medical benchmarks.

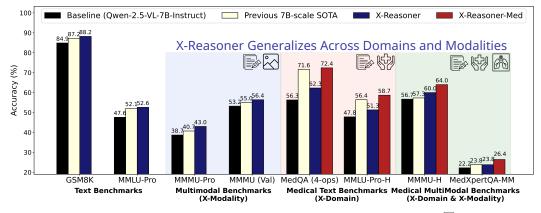


Figure 1: X-REASONER ( blue bars), fine-tuned solely on general domain text , shows strong generalization across both modalities (e.g., multimodality ) and domains (e.g., medicine ), surpassing prior models (Table 7) trained with in-domain multimodal data. X-REASONER-MED ( red bars), its medical-specialized variant, achieves SOTA-level performance on numerous medical benchmarks.

# 1 Introduction

Reasoning has emerged as a foundational capability in language models, paving the way for a new paradigm known as test-time scaling (OpenAI, 2024). Recent proprietary models, such as o3 (OpenAI, 2025), have begun to demonstrate strong multimodal reasoning capabilities. However, existing open-source research primarily focuses on advancing text-only reasoning, employing post-training techniques such as long CoT (Chain-of-Thought) distillation and reinforcement learning with verifiable rewards (DeepSeek-AI et al., 2025; Hu et al., 2025). More recently, a growing body of open-source work has started addressing multimodal reasoning, i.e., extending reasoning to inputs that include both vision and language (Wang et al., 2025a; Meng et al., 2025; Guo et al., 2024). Yet, these multimodal approaches often rely heavily on curating multimodal datasets which are tailored to specific tasks or domains, limiting their generalisability. In parallel, researchers have also investigated domain-specific reasoning, particularly in medicine (Zhang et al., 2025a; Lai et al., 2025; Pan et al., 2025; Su et al., 2025), where models are typically trained on narrowly scoped in-domain data with little capacity to generalize beyond their domain. As a result, how to develop models with reasoning capabilities that generalize across both domains and modalities remains an open question.

In this work, we ask a fundamental, yet under-explored question: *Is reasoning generalizable across modalities and domains?* Specifically, we investigate whether such generalizable reasoning can be achieved through general-domain text-based reasoning post-training. Beyond scientific significance, this question is also motivated by the practical advantages of general domain text-only training: i.e. its compute efficiency and the abundance and verifiability of general-domain textual reasoning data, which together allow us to avoid the cost and complexity of curating multimodal or domain-specific data. Our hypothesis is that text-based post-training, when carefully designed, can impart universal reasoning patterns that robustly transfer across both unseen domains and input modalities.

To investigate our hypothesis, we conduct an extensive empirical study using a two-stage text-only post-training recipe: supervised fine-tuning (SFT) on general-domain text data with distilled long CoTs, followed by reinforcement learning with verifiable rewards (RLVR) using mathematical textual questions. Remarkably, this pure general-domain textual training regimen proves sufficient to instill strong reasoning capabilities, enabling high performance not only on general-domain text-based tasks but also on complex multimodal and domain-specific tasks.. This finding suggests that the core structure of reasoning can indeed be acquired from general-domain text alone.

Building upon these insights, we introduce **X-Reasoner**, a 7B dense vision-language model post-trained with the proposed recipe. Despite being trained only for text-based reasoning, X-Reasoner achieves superior performance on a suite of both text-only and multimodal reasoning benchmarks, outperforming prior state-of-the-art 7B models that were explicitly trained with multimodal reasoning supervision, on challenging tasks including MMMU, MMMU-Pro and MathVista. We further demonstrate that the improvement from X-Reasoner can generalize to specialized domains such as medicine. To boost in-domain performance even further, we explore the impact of incorporating domain-specific textual data. To this end, we introduce **X-Reasoner-Med**, a medical-specialized variant of X-Reasoner, which undergoes additional post-training on medical domain text. X-Reasoner-Med sets new records on numerous textual and multimodal medical tasks.

Our key contributions can be summarized as the following:

# 1. Generalizable Reasoning Study:

- We conduct an in-depth study and find that training reasoning solely on general-domain text yields the most effective generalization across both input modalities and domains.
- We find that combining SFT and RL yields the strongest gains, and that math text data serves as better generalization anchor than domain-specific multimodal data in RL.

#### 2. Introduction of X-REASONER:

- We propose an effective post-training recipe for vision-language reasoning models that relies entirely on general-domain text-based data.
- X-REASONER improves performance across modalities and domains, remarkably, outperforming models trained on multimodal data.

#### 3. Medical Domain Extension via X-REASONER-MED:

 We present X-REASONER-MED, a domain-adapted variant of X-REASONER trained on medical text, setting new 7B-scale records across medical text-only and multimodal tasks.

# 2 A JOURNEY TOWARDS GENERALIZABLE REASONING

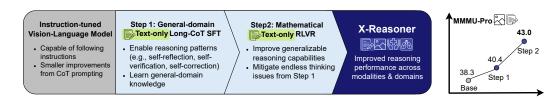


Figure 2: (Left) Our recipe for generalizable reasoning: based on an instruction-tuned VLM, we first conduct SFT on general-domain text data with distilled long CoTs. This is followed by RLVR on mathematical textual questions. This resulting model, X-REASONER, exhibits significantly enhanced reasoning capabilities across modalities and domains. (Right) Model performance on MMMU-Pro (multimodal task) steadily improves at each stage of our recipe.

In this section, we embark on a systematic exploration to understand whether generalizable reasoning can be effectively acquired through general-domain text-based post-training. Here, we define *generalizable reasoning* as the ability to transfer reasoning capabilities not only across different task distributions but also across modalities and domains. To thoroughly address this question, we break it down into two sub-questions corresponding to two predominant post-training strategies used to foster reasoning: SFT and RL. Starting from an instruction-tuned vision-language model (VLM) capable of following instructions yet benefiting less from CoT prompting (see Section 2.1), we perform a detailed empirical study utilizing these two post-training methods. Our objective is to identify a robust and effective recipe that achieves strong, generalizable reasoning capabilities purely through general-domain text-based training. All experiments in this study are initialized from Qwen-2.5-VL-7B, which is also the baseline. Evaluation tasks used are summarized Appendix E.

# 2.1 RQ1: WILL GENERAL-DOMAIN TEXT-ONLY SFT IMPROVE GENERALIZABLE REASONING?

Our first research question investigates whether SFT on general-domain textual data can already enable generalizable reasoning, focusing on (1) the extent to which generalization can occur across domains and modalities, and (2) the essential role of reasoning in enabling such generalization.

Extent of Generalization To examining the extent of the generalization from SFT training, we perform SFT on Qwen-2.5-VL-7B using OpenThoughts-114k (Open Thoughts Team, 2025), a *text-only* dataset covering *general-domain* data including math and science long-CoT reasoning distilled from DeepSeek-R1 (DeepSeek-AI et al., 2025). Results in Table 1 show the SFT models yield consistent performance gains across the following generalization axes: cross-domain (X-domain), cross-modality (X-modality) and the intersection of the two axes (We additionally observe text-only SFT generalizes across distributions/tasks Appendix G). This indicates that SFT with general-domain text-data already shows strong generalization capabilities across modalities and domains.

**Role of CoT Reasoning in Generalization** In Table 1, we observe that reasoning is crucial at inference time (CoT prompt templates are in Appendix D). Even among the baseline models, those equipped with CoT prompting outperform those without it, underscoring that explicit reasoning is a prerequisite for high performance on reasoning-centric tasks. However, the improvement from CoT prompting in the baseline is notably smaller compared with SFT, indicating that the VLM's inherent CoT capability prior to SFT is limited and the long-CoT reasoning learned from SFT is essential to unlock the full reasoning power. To further isolate the contribution of reasoning in SFT training, we compare models trained with and without explicit CoT supervision using the same OpenThoughts data: (1) a non-CoT SFT model trained directly on input-label pairs, and (2) a CoT SFT model trained with reasoning traces. Across all experiments in Table 1, the CoT SFT model consistently outperforms its non-CoT counterpart. Moreover, the CoT SFT models not only perform better indomain/modality but also exhibit stronger transfer capabilities. Notably, the performance lift from CoT SFT over the CoT baseline is substantially larger than the corresponding improvement from non-CoT SFT over the non-CoT baseline across all generation settings. This suggests that explicit reasoning is the key to achieving both the highest performance and the optimal generalization across new domains and modalities.

**Forced-Exiting:** Mitigating Endless Thinking in Long-CoT SFT While long-CoT SFT effectively learns transferrable reasoning patterns, such as self-reflection, verification, and correction (see qualitative analyses in Appendix O), it occasionally leads to endless thinking with non-terminating outputs. To address this, we implement a forced-exiting mechanism inspired by Muennighoff et al. (2025) to append '
 \* after a length threshold is reached. This mechanism effectively mitigates endless thinking and therefore improves final results (See Appendix H for details).

Table 1: Comparing baseline (Qwen-2.5-VL-7B) and SFT models trained on general-domain text-only data with and without CoT on evaluation benchmarks across modalities and domains.

			No	n-CoT		СоТ
Task	Modality	Domain	Baseline	SFT	Baseline	SFT
MMLU-Pro	Textual	General	39.5	39.5 (+0.0)	47.6	50.4 (+2.8)
MedQA (X-domain)	Textual	Medical	49.3	52.1 (+2.8)	50.5	<b>55.2</b> ( <b>+4.7</b> )
MMMU-Pro (X-modality)	Multimodal	General	34.6	36.0 (+1.4)	38.3	40.4 (+2.1)
MMMU-Pro-H (X-modality&domain)	Multimodal	Medical	28.1	30.2 (+2.1)	34.3	<b>37.9</b> ( <b>+3.6</b> )

#### Takeaway 2.1.1

SFT on general-domain text-only data, when enriched with long CoTs, can endow models with generalizable reasoning capabilities that transfer across tasks, domains, and modalities.

# 2.2 RQ2: WILL GENERAL-DOMAIN TEXT-ONLY RL IMPROVE GENERALIZABLE REASONING?

Reinforcement Learning (RL) has become an effective approach for training models to reason. In this section, we explore whether general-domain (particularly mathematical) text-only RL can promote generalizable reasoning.

**Learning Algorithm** We adopt GRPO (Shao et al., 2024) as our reinforcement learning algorithm (Sutton, 1988), which avoids value functions by computing advantages within query-specific groups, making it preferable to methods like PPO (Schulman et al., 2017) (see Appendix B). To enhance training, we apply recent advances (Liu et al., 2025a; Yu et al., 2025): (1) a higher clipping threshold to boost response diversity and prevent entropy collapse; (2) a token-level policy gradient to reduce response-length bias; and (3) minimal or no KL penalty, which benefits long CoT reasoning. For rewards, we use verifiable task accuracy—assigning 1 for semantically correct responses and 0 otherwise—instead of learned reward models, which are prone to reward hacking (Gao et al., 2022). No format rewards are needed, as the model reliably adheres to formatting.

The Role of Training Data: Math Text as a Generalization Anchor A central question in generalizable RL training is what type of training data best supports reasoning generalization? We hypothesize that math textual questions are particularly effective, as math tasks naturally elicit long, structured chains of thought that should benefit transfer across domains and modalities. To test this, we finetune Qwen-2.5-VL-7B with RL on math textual questions from Orz (Hu et al., 2025). We compare this approach with RL trained with popular existing in-domain and multimodal training data including (1) MedQA, a domain-specific medical textual QA dataset . (2) ThinkLite (Wang et al., 2025b), a large-scale curated multimodal general-domain VQA dataset. and (3). OmniMed-VQA, a large-scale multimodal medical-domain VQA dataset (We follow previous studies Pan et al. (2025) to split 80% and 20% of the data as the train and test set). We report results across all evaluation combinations of domain and modality: {general, medical} × {text, multimodal}. For additional reference, we include in-distribution test set results for RL datasets that have corresponding test splits. Specifically, we report results on MathVista testmini, MedQA test and OmniMedVQA test for ThinkLite RL, MedQA RL and OmniMedVQA RL. Results in Table 2 reveal RL trained with math text data achieves the overall best generalization with the highest average performance. Notably, math text RL can achieve better performance in MMMU-Pro (a general-domain multimodal task) than RL trained on general-domain multimodal data (ThinkLite). Similarly, on MMMU-Pro-Health, a medical multimodal task, math text RL outperforms OmniMedVQA RL. We observe that while OmniMedVQA does achieve near-perfect performance on its own test set: 97% accuracy, it fails to generalize to other tasks—even those that are in-domain and multimodal. These findings highlight that math text data offers the most effective foundation for cross-domain and cross-modality generalization, outperforming in-domain multimodal training.

Table 2: Comparing the effect from different training data on RL generalizatio from Qwen-2.5-VL-7B. For some RL data, in-distribution (in-distr.) test results are also shown. Each result reports average accuracy over 5 runs (SD. in Table 16). gen.=general; med.=medical; OMV=OmniMedVQA.

				;				
DI Doto	Domain	Modality	GSM8K	MMMU-Pro	MMLU-Pro-H	I MMMU-Pro-H	Average	In-distr.
KL Data	Domain	Wiodanty	(gen. text)(	gen. multimodal)	(med. text)	(med. multimodal)	(all)	
Baseline	-	-	86.0	38.3	47.8	34.3	51.6	-
math Orz	z general	text	89.0	41.2	51.8	36.9	54.7	-
MedQA	medical	text	86.9	39.7	53.9	34.4	53.7	
ThinkLit	e general	multimoda	1 87.4	40.1	49.8	<b>37.5</b>	53.7	73.0
OMV	medical	multimoda	1 85.1	36.2	45.3	29.0	48.9	97.0

#### Takeaway 2.2.1

216

217

218

219220221222

224225226227228

229 230

231232

233

234

235

236

237

238

239

240

241

242

243

244

245

246

247

248

249

250

251

252

253

254

255

256

257258259260261262

264

265

266

267 268 Math text data provides effective generalization anchor for cross-domain and cross-modality reasoning in RL, outperforming even in-domain multimodal training.

**RL** vs SFT Prior work has positioned RL as a powerful yet volatile method for promoting generalizable reasoning (Chu et al., 2025), while SFT is widely recognized for its stability and efficacy in capturing structured reasoning patterns. In addition, RL is often plagued by training instability and convergence issues, particularly when applied in isolation (Yeo et al., 2025). To better understand their relative strengths, we conduct comparison between RL and SFT in fostering generalization across domain shifts and modality transitions. Specifically, we compare general-domain text-only SFT (trained on general-domain OpenThoughts data) and RL (trained on math questions from Orz), and their combination (SFT + RL). Alongside the general-domain text task (MMLU-Pro), we evaluated the models in three distinct generalization settings: cross-domain (medical text: MMLU-Pro-Health), cross-modality (multimodal: MMMU-Pro), cross domain&modality (multimodal medical: NEJM Image Challenge). In Table 3, we first observe that general-domain SFT and RL can both significantly improve from baseline across all the generalization settings, indicating both SFT and RL can elicit generalizable reasoning. We further notice that pure RL is overall slightly better than SFT. Interestingly, there is a synergy effect when we apply RL after SFT. We hypothesize that it is because RL can benefit from the long and structured reasoning foundation established by SFT, and further refines the model's capabilities via RLVR. This is supported by the observation that SFT + RL maintains the long response length induced by SFT. We also observe that SFT + RL is able to regulate the endless thinking issue from SFT as the percentage of responses that exceeds the maximum length decreases during RL training, as shown in the training response clip ratio in Figure 5. In summary, the hybrid approach, general-domain text-only SFT + RL, achieves the best results across all generalization settings, effectively combining SFT's stability and inductive strength with RL's reward-guided optimization<sup>1</sup>.

Table 3: Comparison of general-domain text-based RL, SFT, and SFT + RL in general-domain textual task (MMLU-Pro) and generalization setups including cross-modality (X-modality), cross-domain (X-domain) and combined cross-domain&modality (X-modality&domain) tasks. SFT is trained with OpenThoughts data and RL is trained with math data. Baseline is Qwen-2.5-VL-7B

Method	MMLU-Pro (G-domain text)			NEJM Image Challenge (X-domain&modality)	Response Len (#words)
Baseline	47.6	47.8	38.3	41.8	122
SFT	50.4	50.4	40.4	45.0	946
RL	52.3	51.8	41.3	45.0	461
SFT + RL	53.3	53.1	42.5	45.7	977

# Takeaway 2.2.2

Combining SFT with RL, both trained on general-domain text-only data, proves to be the most effective strategy for achieving optimal performance and robust generalization.

<sup>&</sup>lt;sup>1</sup>We also conduct a more controlled comparison between SFT and RL, both trained on the same MedQA data, and arrive at the same conclusion (Table 10).

#### 2.3 PUTTING IT ALL TOGETHER: X-REASONER

Our investigation reveals that general-domain text-only post-training, when carefully designed, can drive strong generalizable reasoning across tasks, domains, and modalities. Therefore, we conclude our investigation by consolidating our findings into a coherent training recipe, illustrated in Figure 2, culminating in a powerful generalizable reasoning model named **X-REASONER**. Specifically, initialized with Qwen2.5-VL-7B-Instruct (Bai et al., 2025), our training recipe follows:

Step 1: text-only general-domain Long-CoT SFT. We begin with SFT to elicit explicit structured reasoning using long-CoT traces. The train data is the general-domain open-thoughts/OpenThoughts-114k dataset (Open Thoughts Team, 2025), which contains reasoning traces on math, coding and science questions, distilled by DeepSeek-R1 (DeepSeek-AI et al., 2025) (We also compared with using math data from RL stage for SFT but found worse performance in Appendix J.) We performed SFT for 4 epochs with a learning rate of  $1 \times 10^{-5}$ .

Step 2: text-only math RLVR. After SFT, we further refine our model using RL with verifiable rewards to enhance its reasoning accuracy and generalization. We train our model on Orz-math-57k, a set of 57k mathematical textual questions curated by Hu et al. (2025). During this stage, we set the total training episodes/epochs to 3, use a learning rate of  $3 \times 10^{-6}$ , a global batch size of 128, and sample 8 rollouts per query with a maximum response length of 4,096 tokens.

SFT used 8×40GB A100 GPUs for 8 hours, while RLVR used 32×40GB A100 GPUs for 56 hours. See Appendix C and Appendix N for full training details and the visualized training dynamics.

# 3 A COMPREHENSIVE EVALUATION OF X-REASONER

**Evaluation Setup** To assess the generalizability of X-REASONER, we evaluate its performance across four distinct settings: (1) General-domain text-only tasks; (2) General-domain multimodal tasks (X-modality); (3) Specialized-domain text-only tasks (X-domain); and (4) Specialized-domain multimodal tasks (X-modality&domain) (see Appendix E for details). The baseline is Qwen-2.5-VL-7B. Inference is conducted using the vLLM backend (Kwon et al., 2023). Consistent with recent reproducibility studies (Hochlehnert et al., 2025), we observe variability even under greedy decoding (temperature=0), due to hardware and environment differences. Therefore, while we report greedy decoding results to compare with previous studies, we report average accuracy, majority-vote accuracy, and pass@n accuracy over five runs at temperature 0.3 to ensure robustness and reproducibility. Majority-vote accuracy follows the self-consistency method (Wang et al., 2023) to scale parallel test-time evaluation. Unless noted otherwise, all evaluations use CoT prompting (prompt templates are in Appendix D). Additionally, we apply forced-exiting mechanism as described in Section 2.1, capping output generation at 4,096 tokens, to mitigate endless thinking.

# 3.1 X-REASONER'S CROSS-MODALITY GENERALIZATION

In Figure 3, we assess the cross-modality generalization capabilities of X-REASONER. We first validate its effectiveness on text-only tasks, observing significant performance gains in MMLU-Pro and GSM8K. Moreover, these improvements robustly transfer to multimodal benchmarks, reflected consistently across average, majority vote, and pass@5 accuracy. These results suggest not only superior reasoning ability but also a broader and more effective search space for further improvement.

We further show that X-REASONER achieves SOTA on MMMU, MMMU-Pro and MathVista, while remaining competitive on others in Table 4. Notably, these SOTA models are extensively trained on multimodal data, underscoring the critical finding that text-only reasoning training alone is sufficient—and likely accounts for the majority of learning necessary for effective multimodal reasoning. In Appendix L, we explored continue training X-REASONER with multimodal RL, but results were mixed, underscoring the challenge of curating transferable multimodal data (Wei et al., 2025).

Qualitative analysis in Appendix O shows that X-REASONER consistently produces more sophisticated reasoning than the baseline, exhibiting detailed planning, verification (e.g., "wait" steps), and self-correction. In cross-modality tasks, it effectively integrates visual inputs into step-by-step reasoning. For instance, in Table 18, X-REASONER accurately analyzes all bar values in a plot, avoiding common baseline errors. These examples demonstrate that X-REASONER internalizes general reasoning patterns through text-only training and successfully transfers them across modalities.

# Takeaway 3.2.1

X-REASONER, trained on text-only data, consistently improves multimodal task performance, matching or surpassing prior SOTA trained explicitly with multimodal data.

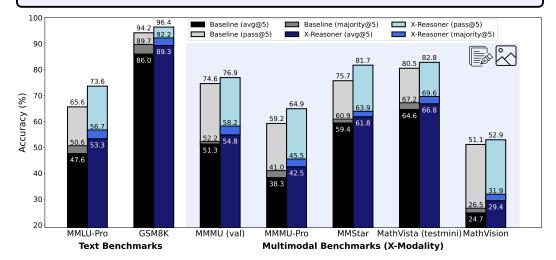


Figure 3: Comparing X-REASONER and baseline on text-only and multi-modal benchmarks (SD reported in Table 14). Despite being trained with text-only data, X-REASONER can significantly improve multi-modal benchmarks, showing the generalization of X-REASONER's reasoning. Table 4: X-REASONER outperforms SOTA multimodal models on the 7B/8B scale on challenging multimodal tasks. All results are based on greedy decoding.

Model	Reasoning Data Source	MMMU (Val)	MMMU-Pro	MathVista (testmini)	MathVision
Qwen-VL-2.5-7B-Instruct (Bai et al., 2025)	-	53.0	38.7	62.8	25.0
R1-Onevision-7B (Yang et al., 2025)	multimodal	-	-	64.1	29.9
MAmmoTH-VL2-7B (Jia et al., 2025)	multimodal	54.7	40.7	68.1	-
MM-Eureka-8B (Meng et al., 2025)	multimodal	49.2	-	67.1	22.2
Mulberry-7B (Yao et al., 2024)	multimodal	55.0	36.8	63.1	-
X-REASONER (7B)	text	56.4	43.0	69.0	29.6

Ablation Study: Is X-REASONER simply solving the text-solvable examples? A potential limitation in evaluating vision-language models is their tendency to rely on text-based shortcuts, solving tasks without genuinely integrating visual information. To rigorously confirm that the crossmodality generalization observed with X-REASONER is not merely due to improved text-only shortcut solutions, we conduct an ablation experiment. Specifically, we identify and remove text-solvable examples and assess whether performance gains persist afterward. To identify these text-solvable examples, we mask visual inputs for multimodal tasks previously evaluated in Section 3.1, performing text-only evaluations using both X-REASONER and the baseline Qwen2.5-VL-7B-Instruct. For each model, we sample three independent responses per question and eliminate examples consistently solved through text alone. Table 5 summarizes the number of remaining examples after removing text-solvable examples for each task, along with the corresponding model performances. While a substantial number of text-solvable instances were identified, these primarily reflect models' textual reasoning shortcuts rather than dataset issues (Yue et al., 2024b). Crucially, X-REASONER maintains performance advantages over the baseline after text-only solvable examples are excluded, affirming true multimodal reasoning capabilities. This confirms that X-REASONER effectively utilizes visual context within the reasoning framework acquired through text-only training.

#### Takeaway 3.2.2

X-REASONER achieves authentic multimodal reasoning capabilities, as evidenced by sustained improvements after excluding text-only solvable examples.

Table 5: Comparing X-REASONER and baseline performance after removing text-solvable examples. The improvement of X-REASONER remains, indicating true multimodal generalizability.

Task	#original - #text-solvable = #	Baseline	X-REASONER
MMMU	900 - 308 = 592	39.3	41.4
MMMU-Pro	1730 - 259 = 1471	33.4	36.4
MathVista (testmini)	1000 - 257 = 743	57.9	60.6
MathVision	3040 - 448 = 2592	18.6	21.8
MMStar	1500 - 259 = 1241	56.6	59.0

#### 3.2 X-REASONER IN MEDICINE: A CROSS-MODALITY AND CROSS-DOMAIN STUDY

In this section, we examine the cross-domain and cross-modality transfer capabilities of X-REASONER, specifically within medical contexts. While X-REASONER is trained exclusively on general-domain text data, we further probe the benefits of domain-specific adaptation by developing X-REASONER-MED, which extends X-REASONER with additional training using medical text data.

**Evaluation Setup** Our evaluation includes three text-only medical tasks: MMLU-Pro-Health (the healthcare subset of MMLU-Pro (Wang et al., 2024b), selected following the setup in (Chen et al., 2024a)), MedQA (the original USMLE version), and MedQA (4-ops: the four-choice version). For multimodal medical evaluations, we utilize healthcare subsets of MMMU (Yue et al., 2024a) and MMMU-Pro (Yue et al., 2024b), designated as MMMU-Health and MMMU-Pro-Health respectively. We also include MedXpertQA-MM (Zuo et al., 2025), OmniMedVQA (Hu et al., 2024) and NEJM Image Challenge (New England Journal of Medicine, 2025), which are specifically designed to evaluate medical knowledge and reasoning.

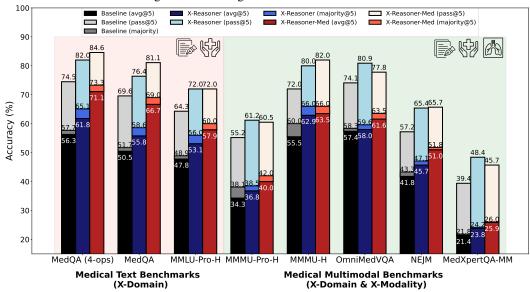


Figure 4: Comparing X-REASONER, X-REASONER-MED and baseline on text and multimodal medical benchmarks (SD. reported in Table 15). X-REASONER, trained with general-domain text-only data brings consistent improvement across medical tasks. X-REASONER-MED, obtained by continued training of X-REASONER on medical text data, further improves performance.

Results Figure 4 shows X-REASONER demonstrates robust cross-domain and cross-modality generalization capabilities, surpassing baseline models on both textual and multimodal medical tasks. Remarkably, as detailed in Figure 1, X-REASONER surpassing or matching previous SOTA on MedXpertQA-MM and MMMU-Health, despite previous SOTA models being explicitly trained on multimodal medical data. Qualitative assessments in Appendix O further illustrate X-REASONER's effective integration of visual information and medical domain-specific reasoning. As an example, X-REASONER accurately identifies medical patterns, such as correctly recognizing white matter abnormalities indicative of progressive multifocal leukoencephalopathy in histology slides (Table 19).

#### Takeaway 3.3.1

X-REASONER substantially enhances medical task performance, confirming its strong capability for cross-domain and cross-modality generalization.

**X-REASONER-MED:** Enhancing Medical Performance We investigate whether additional medical-domain text data can further enhance X-REASONER's medical performance. To explore this, we extend X-REASONER's training with text-only MedQA data. Specifically, starting from X-REASONER, we perform SFT with distilled CoTs from QwQ-32B (Qwen Team, 2025), followed by RLVR on the same data (For ablation, we also compared MedQA SFT + RL with X-REASONER-MED in Appendix K, showing X-REASONER-MED is better, highlighting the benefit of starting domain adaptation from a generalist X-REASONER).

The resulting model, X-REASONER-MED, achieves further improvements across all medical benchmarks. As depicted in Figure 4, X-REASONER-MED consistently surpasses X-REASONER in terms of average and majority vote accuracies. Notably, X-REASONER sometimes attains higher pass@n scores, suggesting it explores a broader search space. Conversely, X-REASONER-MED, benefiting from targeted medical-domain fine-tuning, already leverages this search space more effectively but potentially with reduced room for further gains. Nevertheless, as highlighted in Figure 1, X-REASONER-MED sets new SOTA performance for both text-only and multimodal medical tasks, validating our hypothesis that combining general text-based reasoning with domain-specific text-based fine-tuning unlocks substantial additional performance gains for specialized domains.

#### Takeaway 3.3.2

X-REASONER-MED, obtained by further training X-REASONER on medical text, improves further and sets new SOTA on both text and multimodal medical benchmarks.

#### 4 RELATED WORK

In RL-based learning of multimodal reasoning, most methods such as VFT (Liu et al., 2025b), MM-Eureka (Meng et al., 2025), Vision-R1 (Huang et al., 2025a), R1-V (Chen et al., 2025), and Zhou et al. (2025); Deng et al. (2025); Wan et al. (2025) refine reasoning in VLM with multi-modal training data. Peng et al. (2025b) present a two-stage RL approach that leverages both text-based and multimodal data. On the SFT side, reasoning is commonly distilled from captions or responses synthesized by VLMs. Methods such as MaMMOTH (Guo et al., 2024; Jia et al., 2025), Vision-R1 (Huang et al., 2025a), R1-OneVision (Yang et al., 2025), and Llava-CoT (Xu et al., 2024) follow this strategy to infuse reasoning into multimodal models during SFT. Alternatively, some methods incorporate visual grounding by coupling a text-based reasoning model with a vision encoder (Peng et al., 2025a). Closest to our study, Du et al. (2025) also explores text-only training for multimodal tasks, though their setting is limited to SFT and general-domain evaluation. Recently, there has also been growing interest in applying reasoning techniques to specialized domains such the medical domain, initially focusing on the text modality (Zhang et al., 2025a; Huang et al., 2025b; Chen et al., 2024a). Subsequently, researchers have begun exploring RL-based training on multimodal medical datasets to enhance multimodal reasoning performance in the medical domain, e.g., Pan et al. (2025) and Lai et al. (2025).

### 5 Conclusion

This study demonstrates that general domain text-only SFT+RL is the most effective recipe for learning generalizable reasoning even for multi-modal and out-of-domain settings. Building on this insight, we introduce X-REASONER, a simple yet effective post-training recipe that enhances the reasoning capabilities of VLMs using only general-domain text-based supervision. Through extensive experiments, we show that X-REASONER generalizes effectively across modalities and domains, surpassing prior SOTA trained with in-domain multimodal data. We further show X-REASONER serves as a strong foundation for domain specialization by introducing X-REASONER-MED, a variant further trained on medical text, which achieves new SOTA on various medical benchmarks across both text-only and multimodal settings. We leave to future work the exploration of continued indomain multimodal SFT/RL and we provide detailed discussion on our limitations in Appendix A.

#### REFERENCES

- Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, Humen Zhong, Yuanzhi Zhu, Mingkun Yang, Zhaohai Li, Jianqiang Wan, Pengfei Wang, Wei Ding, Zheren Fu, Yiheng Xu, Jiabo Ye, Xi Zhang, Tianbao Xie, Zesen Cheng, Hang Zhang, Zhibo Yang, Haiyang Xu, and Junyang Lin. Qwen2.5-VL Technical Report, 2025. URL http://arxiv.org/abs/2502.13923.
- Junying Chen, Zhenyang Cai, Ke Ji, Xidong Wang, Wanlong Liu, Rongsheng Wang, Jianye Hou, and Benyou Wang. HuatuoGPT-o1, Towards Medical Complex Reasoning with LLMs, 2024a. URL http://arxiv.org/abs/2412.18925.
- Liang Chen, Lei Li, Haozhe Zhao, Yifan Song, and Vinci. R1-v: Reinforcing super generalization ability in vision-language models with less than \$3. https://github.com/Deep-Agent/R1-v, 2025. Accessed: 2025-02-02.
- Lin Chen, Jinsong Li, Xiaoyi Dong, Pan Zhang, Yuhang Zang, Zehui Chen, Haodong Duan, Jiaqi Wang, Yu Qiao, Dahua Lin, and Feng Zhao. Are We on the Right Way for Evaluating Large Vision-Language Models? In *Proceedings of Conference on Neural Information Processing Systems (NeurIPS)*, 2024b. URL http://arxiv.org/abs/2403.20330.
- Zui Chen, Yezeng Chen, Jiaqi Han, Zhijie Huang, Ji Qi, and Yi Zhou. An Empirical Study of Data Ability Boundary in LLMs' Math Reasoning, 2024c. URL http://arxiv.org/abs/2403.00799.
- Tianzhe Chu, Yuexiang Zhai, Jihan Yang, Shengbang Tong, Saining Xie, Dale Schuurmans, Quoc V. Le, Sergey Levine, and Yi Ma. SFT Memorizes, RL Generalizes: A Comparative Study of Foundation Model Post-training, 2025. URL http://arxiv.org/abs/2501.17161.
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training Verifiers to Solve Math Word Problems, 2021. URL http://arxiv.org/abs/2110.14168.
- Noel C. F. Codella, Ying Jin, Shrey Jain, Yu Gu, Ho Hin Lee, Asma Ben Abacha, Alberto Santamaria-Pang, Will Guyman, Naiteek Sangani, Sheng Zhang, Hoifung Poon, Stephanie Hyland, Shruthi Bannur, Javier Alvarez-Valle, Xue Li, John Garrett, Alan McMillan, Gaurav Rajguru, Madhu Maddi, Nilesh Vijayrania, Rehaan Bhimai, Nick Mecklenburg, Rupal Jain, Daniel Holstein, Naveen Gaur, Vijay Aski, Jenq-Neng Hwang, Thomas Lin, Ivan Tarapov, Matthew Lungren, and Mu Wei. MedImageInsight: An Open-Source Embedding Model for General Domain Medical Imaging, 2024. URL http://arxiv.org/abs/2410.06542.
- DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, and 190 additional authors. DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning, 2025. URL http://arxiv.org/abs/2501.12948.
- Yihe Deng, Hritik Bansal, Fan Yin, Nanyun Peng, Wei Wang, and Kai-Wei Chang. OpenVLThinker: An Early Exploration to Complex Vision-Language Reasoning via Iterative Self-Improvement, 2025. URL http://arxiv.org/abs/2503.17352.
- Yifan Du, Zikang Liu, Yifan Li, Wayne Xin Zhao, Yuqi Huo, Bingning Wang, Weipeng Chen, Zheng Liu, Zhongyuan Wang, and Ji-Rong Wen. Virgo: A preliminary exploration on reproducing ollike mllm, 2025. URL https://arxiv.org/abs/2501.01904.
- Leo Gao, John Schulman, and Jacob Hilton. Scaling Laws for Reward Model Overoptimization, 2022. URL http://arxiv.org/abs/2210.10760.
- Gemma Team, Morgane Riviere, Shreya Pathak, Pier Giuseppe Sessa, Cassidy Hardin, Surya Bhupatiraju, Léonard Hussenot, Thomas Mesnard, Bobak Shahriari, Alexandre Ramé, and 188 additional authors. Gemma 2: Improving Open Language Models at a Practical Size, 2024. URL http://arxiv.org/abs/2408.00118.

- Jarvis Guo, Tuney Zheng, Yuelin Bai, Bo Li, Yubo Wang, King Zhu, Yizhi Li, Graham Neubig, Wenhu Chen, and Xiang Yue. MAmmoTH-VL: Eliciting Multimodal Reasoning with Instruction Tuning at Scale, 2024. URL http://arxiv.org/abs/2412.05237.
  - Andreas Hochlehnert, Hardik Bhatnagar, Vishaal Udandarao, Samuel Albanie, Ameya Prabhu, and Matthias Bethge. A Sober Look at Progress in Language Model Reasoning: Pitfalls and Paths to Reproducibility, 2025. URL http://arxiv.org/abs/2504.07086.
  - Jingcheng Hu, Yinmin Zhang, Qi Han, Daxin Jiang, Xiangyu Zhang, and Heung-Yeung Shum. Open-reasoner-zero: An open source approach to scaling up reinforcement learning on the base model, 2025. URL https://arxiv.org/abs/2503.24290.
  - Yutao Hu, Tianbin Li, Quanfeng Lu, Wenqi Shao, Junjun He, Yu Qiao, and Ping Luo. OmniMed-VQA: A New Large-Scale Comprehensive Evaluation Benchmark for Medical LVLM. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2024. URL http://arxiv.org/abs/2402.09181.
  - Jiaxin Huang, Shixiang Gu, Le Hou, Yuexin Wu, Xuezhi Wang, Hongkun Yu, and Jiawei Han. Large Language Models Can Self-Improve. In *Proceedings of Conference on Empirical Methods in Natural Language Processing (EMNLP)*, 2023. URL https://aclanthology.org/2023.emnlp-main.67.
  - Wenxuan Huang, Bohan Jia, Zijie Zhai, Shaosheng Cao, Zheyu Ye, Fei Zhao, Zhe Xu, Yao Hu, and Shaohui Lin. Vision-R1: Incentivizing Reasoning Capability in Multimodal Large Language Models, 2025a. URL http://arxiv.org/abs/2503.06749.
  - Xiaoke Huang, Juncheng Wu, Hui Liu, Xianfeng Tang, and Yuyin Zhou. m1: Unleash the potential of test-time scaling for medical reasoning with large language models, 2025b. URL https://arxiv.org/abs/2504.00869.
  - Yiming Jia, Jiachen Li, Xiang Yue, Bo Li, Ping Nie, Kai Zou, and Wenhu Chen. VisualWebInstruct: Scaling up Multimodal Instruction Data through Web Search, 2025. URL http://arxiv.org/abs/2503.10582.
  - Di Jin, Eileen Pan, Nassim Oufattole, Wei-Hung Weng, Hanyi Fang, and Peter Szolovits. What disease does this patient have? a large-scale open domain question answering dataset from medical exams. *Applied Sciences*, 11(14):6421, 2021.
  - Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023.
  - Yuxiang Lai, Jike Zhong, Ming Li, Shitian Zhao, and Xiaofeng Yang. Med-R1: Reinforcement Learning for Generalizable Medical Reasoning in Vision-Language Models, 2025. URL http://arxiv.org/abs/2503.13939.
  - Chunyuan Li, Cliff Wong, Sheng Zhang, Naoto Usuyama, Haotian Liu, Jianwei Yang, Tristan Naumann, Hoifung Poon, and Jianfeng Gao. Llava-med: Training a large language-and-vision assistant for biomedicine in one day. In A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine (eds.), *Advances in Neural Information Processing Systems*, volume 36, pp. 28541–28564. Curran Associates, Inc., 2023. URL https://proceedings.neurips.cc/paper\_files/paper/2023/file/5abcdf8ecdcacba028c6662789194572-Paper-Datasets\_and\_Benchmarks.pdf.
  - Zichen Liu, Changyu Chen, Wenjun Li, Penghui Qi, Tianyu Pang, Chao Du, Wee Sun Lee, and Min Lin. Understanding R1-Zero-Like Training: A Critical Perspective, 2025a. URL http://arxiv.org/abs/2503.20783.
    - Ziyu Liu, Zeyi Sun, Yuhang Zang, Xiaoyi Dong, Yuhang Cao, Haodong Duan, Dahua Lin, and Jiaqi Wang. Visual-rft: Visual reinforcement fine-tuning. *arXiv preprint arXiv:2503.01785*, 2025b.

- Ilya Loshchilov and Frank Hutter. Decoupled Weight Decay Regularization. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2019. URL http://arxiv.org/abs/1711.05101.
  - Pan Lu, Hritik Bansal, Tony Xia, Jiacheng Liu, Chunyuan Li, Hannaneh Hajishirzi, Hao Cheng, Kai-Wei Chang, Michel Galley, and Jianfeng Gao. MathVista: Evaluating Mathematical Reasoning of Foundation Models in Visual Contexts. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2024. URL http://arxiv.org/abs/2310.02255.
  - Renqian Luo, Liai Sun, Yingce Xia, Tao Qin, Sheng Zhang, Hoifung Poon, and Tie-Yan Liu. Biogpt: generative pre-trained transformer for biomedical text generation and mining. *Briefings in bioinformatics*, 23(6):bbac409, 2022.
  - Fanqing Meng, Lingxiao Du, Zongkai Liu, Zhixiang Zhou, Quanfeng Lu, Daocheng Fu, Tiancheng Han, Botian Shi, Wenhai Wang, Junjun He, Kaipeng Zhang, Ping Luo, Yu Qiao, Qiaosheng Zhang, and Wenqi Shao. MM-Eureka: Exploring the Frontiers of Multimodal Reasoning with Rule-based Reinforcement Learning, 2025. URL http://arxiv.org/abs/2503.07365.
  - Niklas Muennighoff, Zitong Yang, Weijia Shi, Xiang Lisa Li, Li Fei-Fei, Hannaneh Hajishirzi, Luke Zettlemoyer, Percy Liang, Emmanuel Candès, and Tatsunori Hashimoto. S1: Simple test-time scaling, 2025. URL http://arxiv.org/abs/2501.19393.
  - Robert Osazuwa Ness, Katie Matton, Hayden Helm, Sheng Zhang, Junaid Bajwa, Carey E. Priebe, and Eric Horvitz. Medfuzz: Exploring the robustness of large language models in medical question answering, 2024. URL https://arxiv.org/abs/2406.06573.
  - New England Journal of Medicine. Image challenge, 2025. URL https://www.nejm.org/image-challenge. Accessed: 2025-05-02.
  - Harsha Nori, Yin Tat Lee, Sheng Zhang, Dean Carignan, Richard Edgar, Nicolo Fusi, Nicholas King, Jonathan Larson, Yuanzhi Li, Weishung Liu, Renqian Luo, Scott Mayer McKinney, Robert Osazuwa Ness, Hoifung Poon, Tao Qin, Naoto Usuyama, Chris White, and Eric Horvitz. Can Generalist Foundation Models Outcompete Special-Purpose Tuning? Case Study in Medicine, 2023. URL http://arxiv.org/abs/2311.16452.
  - Harsha Nori, Naoto Usuyama, Nicholas King, Scott Mayer McKinney, Xavier Fernandes, Sheng Zhang, and Eric Horvitz. From Medprompt to o1: Exploration of Run-Time Strategies for Medical Challenge Problems and Beyond, 2024. URL http://arxiv.org/abs/2411.03590.
  - Open Thoughts Team. Open Thoughts, 2025. URL https://www.open-thoughts.ai/.
  - OpenAI. Openai o1 system card, 2024. URL https://arxiv.org/abs/2412.16720.
  - OpenAI. Openai o3 and o4-mini system card. https://cdn.openai.com/pdf/2221c875-02dc-4789-800b-e7758f3722c1/o3-and-o4-mini-system-card.pdf, 2025. Accessed: 2025-04-29.
  - Pallets. Jinja. https://github.com/pallets/jinja, 2024.
  - Jiazhen Pan, Che Liu, Junde Wu, Fenglin Liu, Jiayuan Zhu, Hongwei Bran Li, Chen Chen, Cheng Ouyang, and Daniel Rueckert. MedVLM-R1: Incentivizing Medical Reasoning Capability of Vision-Language Models (VLMs) via Reinforcement Learning, 2025. URL http://arxiv.org/abs/2502.19634.
  - Yi Peng, Chris, Xiaokun Wang, Yichen Wei, Jiangbo Pei, Weijie Qiu, Ai Jian, Yunzhuo Hao, Jiachun Pan, Tianyidan Xie, Li Ge, Rongxian Zhuang, Xuchen Song, Yang Liu, and Yahui Zhou. Skywork rlv: Pioneering multimodal reasoning with chain-of-thought. https://github.com/SkyworkAI/Skywork-R1V/blob/main/report/Skywork\_R1V.pdf, 2025a. URL https://huggingface.co/Skywork/Skywork-R1V-38B.
  - Yingzhe Peng, Gongrui Zhang, Miaosen Zhang, Zhiyuan You, Jie Liu, Qipeng Zhu, Kai Yang, Xingzhong Xu, Xin Geng, and Xu Yang. Lmm-r1: Empowering 3b lmms with strong reasoning abilities through two-stage rule-based rl. *arXiv* preprint arXiv:2503.07536, 2025b.

- Hoifung Poon, Tristan Naumann, Sheng Zhang, and Javier González Hernández. Precision health in the age of large language models. In *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, KDD '23, pp. 5825–5826, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400701030. doi: 10.1145/3580305.3599568. URL https://doi.org/10.1145/3580305.3599568.
- Qwen Team. QwQ-32B: Embracing the Power of Reinforcement Learning, 2025. URL https://qwenlm.github.io/blog/qwq-32b/.
- John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal Policy Optimization Algorithms, 2017. URL http://arxiv.org/abs/1707.06347.
- Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang, Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. DeepSeekMath: Pushing the Limits of Mathematical Reasoning in Open Language Models, 2024. URL http://arxiv.org/abs/2402.03300.
- Yanzhou Su, Tianbin Li, Jiyao Liu, Chenglong Ma, Junzhi Ning, Cheng Tang, Sibo Ju, Jin Ye, Pengcheng Chen, Ming Hu, Shixiang Tang, Lihao Liu, Bin Fu, Wenqi Shao, Xiaowei Hu, Xiangwen Liao, Yuanfeng Ji, and Junjun He. GMAI-VL-R1: Harnessing Reinforcement Learning for Multimodal Medical Reasoning, 2025. URL http://arxiv.org/abs/2504.01886.
- Richard S. Sutton. Learning to predict by the methods of temporal differences. *Machine Learning*, 3:9–44, 1988. URL http://link.springer.com/10.1007/BF00115009.
- Zhongwei Wan, Zhihao Dou, Che Liu, Yu Zhang, Dongfei Cui, Qinjian Zhao, Hui Shen, Jing Xiong, Yi Xin, Yifan Jiang, et al. Srpo: Enhancing multimodal llm reasoning via reflection-aware reinforcement learning. *arXiv preprint arXiv:2506.01713*, 2025.
- Haozhe Wang, Chao Qu, Zuming Huang, Wei Chu, Fangzhen Lin, and Wenhu Chen. Vlrethinker: Incentivizing self-reflection of vision-language models with reinforcement learning. *arXiv* preprint arXiv:2504.08837, 2025a.
- Ke Wang, Junting Pan, Weikang Shi, Zimu Lu, Houxing Ren, Aojun Zhou, Mingjie Zhan, and Hongsheng Li. Measuring multimodal mathematical reasoning with math-vision dataset. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024a. URL https://openreview.net/forum?id=QWTCcxMpPA.
- Xiyao Wang, Zhengyuan Yang, Chao Feng, Hongjin Lu, Linjie Li, Chung-Ching Lin, Kevin Lin, Furong Huang, and Lijuan Wang. Sota with less: Mcts-guided sample selection for data-efficient visual reasoning self-improvement. *arXiv preprint arXiv:2504.07934*, 2025b.
- Xuezhi Wang, Jason Wei, Dale Schuurmans, Quoc Le, Ed Chi, Sharan Narang, Aakanksha Chowdhery, and Denny Zhou. Self-Consistency Improves Chain of Thought Reasoning in Language Models. In *Proceedings of International Conference on Learning Representations (ICLR)*, 2023. URL http://arxiv.org/abs/2203.11171.
- Yubo Wang, Xueguang Ma, Ge Zhang, Yuansheng Ni, Abhranil Chandra, Shiguang Guo, Weiming Ren, Aaran Arulraj, Xuan He, Ziyan Jiang, et al. Mmlu-pro: A more robust and challenging multitask language understanding benchmark. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024b.
- Yana Wei, Liang Zhao, Jianjian Sun, Kangheng Lin, Jisheng Yin, Jingcheng Hu, Yinmin Zhang, En Yu, Haoran Lv, Zejia Weng, et al. Open vision reasoner: Transferring linguistic cognitive behavior for visual reasoning. *arXiv preprint arXiv:2507.05255*, 2025.
- Yiqing Xie, Sheng Zhang, Hao Cheng, Pengfei Liu, Zelalem Gero, Cliff Wong, Tristan Naumann, Hoifung Poon, and Carolyn Rose. Doclens: Multi-aspect fine-grained evaluation for medical text generation. *arXiv preprint arXiv:2311.09581*, 2023.
- Guowei Xu, Peng Jin, Li Hao, Yibing Song, Lichao Sun, and Li Yuan. LLaVA-o1: Let Vision Language Models Reason Step-by-Step, 2024. URL http://arxiv.org/abs/2411.10440.

- Yi Yang, Xiaoxuan He, Hongkun Pan, Xiyan Jiang, Yan Deng, Xingtao Yang, Haoyu Lu, Dacheng Yin, Fengyun Rao, Minfeng Zhu, et al. R1-onevision: Advancing generalized multimodal reasoning through cross-modal formalization. *arXiv* preprint arXiv:2503.10615, 2025.
- Huanjin Yao, Jiaxing Huang, Wenhao Wu, Jingyi Zhang, Yibo Wang, Shunyu Liu, Yingjie Wang, Yuxin Song, Haocheng Feng, Li Shen, et al. Mulberry: Empowering mllm with o1-like reasoning and reflection via collective monte carlo tree search. *arXiv preprint arXiv:2412.18319*, 2024.
- Edward Yeo, Yuxuan Tong, Morry Niu, Graham Neubig, and Xiang Yue. Demystifying long chain-of-thought reasoning in llms. 2025. *URL https://arxiv. org/pdf/2502.03373*, 2025.
- Qiying Yu, Zheng Zhang, Ruofei Zhu, Yufeng Yuan, Xiaochen Zuo, Yu Yue, Tiantian Fan, Gaohong Liu, Lingjun Liu, Xin Liu, Haibin Lin, Zhiqi Lin, Bole Ma, Guangming Sheng, Yuxuan Tong, Chi Zhang, Mofan Zhang, Wang Zhang, Hang Zhu, Jinhua Zhu, Jiaze Chen, Jiangjie Chen, Chengyi Wang, Hongli Yu, Weinan Dai, Yuxuan Song, Xiangpeng Wei, Hao Zhou, Jingjing Liu, Wei-Ying Ma, Ya-Qin Zhang, Lin Yan, Mu Qiao, Yonghui Wu, and Mingxuan Wang. DAPO: An Open-Source LLM Reinforcement Learning System at Scale, 2025. URL http://arxiv.org/abs/2503.14476.
- Xiang Yue, Yuansheng Ni, Kai Zhang, Tianyu Zheng, Ruoqi Liu, Ge Zhang, Samuel Stevens, Dongfu Jiang, Weiming Ren, Yuxuan Sun, et al. Mmmu: A massive multi-discipline multi-modal understanding and reasoning benchmark for expert agi. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 9556–9567, 2024a.
- Xiang Yue, Tianyu Zheng, Yuansheng Ni, Yubo Wang, Kai Zhang, Shengbang Tong, Yuxuan Sun, Botao Yu, Ge Zhang, Huan Sun, et al. Mmmu-pro: A more robust multi-discipline multimodal understanding benchmark. *arXiv preprint arXiv:2409.02813*, 2024b.
- Juan Manuel Zambrano Chaves, Shih-Cheng Huang, Yanbo Xu, Hanwen Xu, Naoto Usuyama, Sheng Zhang, Fei Wang, Yujia Xie, Mahmoud Khademi, Ziyi Yang, Hany Awadalla, Julia Gong, Houdong Hu, Jianwei Yang, Chunyuan Li, Jianfeng Gao, Yu Gu, Cliff Wong, Mu Wei, Tristan Naumann, Muhao Chen, Matthew P. Lungren, Akshay Chaudhari, Serena Yeung-Levy, Curtis P. Langlotz, Sheng Wang, and Hoifung Poon. A clinically accessible small multimodal radiology model and evaluation metric for chest x-ray findings. *Nature Communications*, 16(1), April 2025. ISSN 2041-1723. doi: 10.1038/s41467-025-58344-x. URL http://dx.doi.org/10.1038/s41467-025-58344-x.
- Eric Zelikman, Yuhuai Wu, Jesse Mu, and Noah D. Goodman. STaR: Bootstrapping Reasoning With Reasoning. In *Proceedings of Conference on Neural Information Processing Systems (NeurIPS)*, 2022. URL http://arxiv.org/abs/2203.14465.
- Sheng Zhang, Qianchu Liu, Guanghui Qin, Tristan Naumann, and Hoifung Poon. Med-RLVR: Emerging Medical Reasoning from a 3B base model via reinforcement Learning, 2025a. URL http://arxiv.org/abs/2502.19655.
- Sheng Zhang, Yanbo Xu, Naoto Usuyama, Hanwen Xu, Jaspreet Bagga, Robert Tinn, Sam Preston, Rajesh Rao, Mu Wei, Naveen Valluri, et al. A multimodal biomedical foundation model trained from fifteen million image–text pairs. *NEJM AI*, 2(1):AIoa2400640, 2025b.
- Hengguang Zhou, Xirui Li, Ruochen Wang, Minhao Cheng, Tianyi Zhou, and Cho-Jui Hsieh. R1-Zero's "Aha Moment" in Visual Reasoning on a 2B Non-SFT Model, 2025. URL http://arxiv.org/abs/2503.05132.
- Yuxin Zuo, Shang Qu, Yifei Li, Zhangren Chen, Xuekai Zhu, Ermo Hua, Kaiyan Zhang, Ning Ding, and Bowen Zhou. MedXpertQA: Benchmarking Expert-Level Medical Reasoning and Understanding, 2025. URL http://arxiv.org/abs/2501.18362.

#### A LIMITATIONS

 While we show X-REASONER effectively equips vision-language models with generalizable reasoning capabilities, we acknowledge several limitations that offer opportunities for future work:

**Base Model Constraints** Prior studies have emphasized the importance of starting from pretrained base checkpoints, rather than instruction-tuned models, to better incentivize the emergence of reasoning behaviors (DeepSeek-AI et al., 2025; Hu et al., 2025). However, in our case, we are constrained by computational resources and the lack of base VLMs in the recent open-source releases, limiting our ability to empirically validate these claims.

**Model Scale and Backbone Diversity** Prior work suggests that larger models tend to exhibit stronger reasoning capabilities (DeepSeek-AI et al., 2025). However, due to computational constraints, our model size is limited to 7B parameters. We also focused exclusively on the Qwen-VL series and did not evaluate other publicly available VLMs.

Task Scope Our evaluation primarily targets mathematical questions and multiple-choice questions across general and medical domains. While these benchmarks provide clear, verifiable supervision for assessing reasoning capabilities, they do not capture the full spectrum of real-world reasoning challenges. In particular, we have not tested our approach on open-ended generation, interactive dialogue, or instruction-following scenarios. Understanding how reasoning generalizes to such unconstrained settings remains an important area for future exploration. Our evaluation settings also focus on two modalities—text and vision—which are currently the most central to vision-language foundation models. Extending this framework to additional modalities such as audio and video remains an important and valuable direction for future work

#### B GRPO

Let  $\pi_{\theta}$  be a vision language model (VLM) based on decoder-only transformers and parameterized by  $\theta$ . It takes as input a sequence of tokens, denoted by  $\mathbf{q}$ , such as a question, and autoregressively decodes the response, denoted by  $\mathbf{o}$ . Optionally,  $\pi_{\theta}$  can also take visual features, such as pictures, as input that is tokenized by a vision encoder. However, visual features are not included in our training paradigm, and  $\mathbf{q}$  during training is supposed to be natural languages only. We use text-only math datasets for training. Let  $\mathcal{D}$  be a dataset and  $(\mathbf{q}, \mathbf{a}) \in \mathcal{D}$  be pairs of questions and answers.

In Group Relative Policy Optimization (Shao et al., 2024, GRPO), for a given query  $\mathbf{q}$ , the policy model samples a group of responses, and the token-level advantage  $\hat{A}_{i,t}$  for the *i*-th response is estimated by normalizing its reward  $r_i$  relative to the group rewards  $\mathbf{r}$ :

$$\hat{A}_{i,t} = \frac{r_i - \text{mean}(\mathbf{r})}{\text{std}(\mathbf{r})},\tag{1}$$

Similar to PPO (Schulman et al., 2017), GRPO employs a clipped surrogate objective but includes a KL-divergence penalty term directly in its loss function to encourage stability:

$$\mathcal{J}_{GRPO}(\theta) = \mathbb{E}_{\mathbf{q} \sim \mathcal{Q}, \{\mathbf{o}_{i}\}_{i=1}^{G} \sim \pi_{\theta_{\text{old}}}(\cdot | \mathbf{q})} \left\{ \frac{1}{G} \sum_{i=1}^{G} \frac{1}{|\mathbf{o}_{i}|} \sum_{t=1}^{|\mathbf{o}_{i}|} \min \left[ \frac{\pi_{\theta}(o_{i,t} \mid \mathbf{q}, \mathbf{o}_{i,< t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid \mathbf{q}, \mathbf{o}_{i,< t})} \hat{A}_{i,t}, \right. \\
\left. \text{clip} \left( \frac{\pi_{\theta}(o_{i,t} \mid \mathbf{q}, \mathbf{o}_{i,< t})}{\pi_{\theta_{\text{old}}}(o_{i,t} \mid \mathbf{q}, \mathbf{o}_{i,< t})} \hat{A}_{i,t}, 1 - \epsilon, 1 + \epsilon \right) \right] - \beta \mathbb{D}_{KL} \left[ \pi_{\theta} \| \pi_{\text{ref}} \right] \right\}, \tag{2}$$

where  $\pi_{\theta}$  is the policy model, i.e., VLM. For a query  $\mathbf{q}$ , we sample G outputs  $\{\mathbf{o}_1, \dots, \mathbf{o}_G\}$  from the old policy model  $\pi_{\theta_{\text{old}}}$ . Clip ratio  $\epsilon$  and  $\beta$  are hyper-parameters and  $\pi_{\text{ref}}$  is the reference VLM.

#### C Hyperparameters

In this section, we discuss the hyperparameters used in our SFT and RL experiments.

# C.1 SUPERVISED FINE-TUNING

For the SFT experiments, we use the AdamW optimizer (Loshchilov & Hutter, 2019) with a learning rate of  $1 \times 10^{-5}$ , weight decay of 0.0,  $\beta_1 = 0.9$  and  $\beta_2 = 0.999$ . We adopt a multiplicative learning rate scheduler with a decay rate of 0.8 for each epoch. The training batch size is set as 4 per device and we used 32 GPUs in total. For training efficiency, we remove examples that exceed 4096 tokens and result in around 40k training examples. Each dataset will be trained for 4 epochs.

# C.2 REINFORCEMENT LEARNING

Throughout our experiments, we set KL coefficient  $\beta=1.0\times 10^{-2}$  and the clip ratio  $\epsilon=0.2$ . For each example, we sample 8 responses with a maximum length of 4096 tokens and sampling temperature of 1.0.

When updating the actor model, we use AdamW (Loshchilov & Hutter, 2019) and set the learning rate as  $3.0 \times 10^{-6}$  and weight decay as  $1.0 \times 10^{-2}$ . A warm-up learning rate scheduler is used by using 10% of the total training steps. Gradient norm is applied with a threshold of 1.0. A global batch size (calculated across all devices) is set as 128. All the training are stopped on the convergence of the reward value on the training set.

# D PROMPT TEMPLATES

Below are the prompt templates in Jinja format Pallets (2024) used in training and evaluation. Both Qwen-2.5-VL-7B-Instruct baseline and X-REASONER are able to successfully follow instructions to enclose answers within <code><answer> </answer></code> tags with a success rate of around 99% . Therefore the improvements from X-REASONER are not attributable to formatting.

# **Prompt Template for Training**

```
844
845
846
```

```
You will solve a problem/request. You should provide your thoughts within <think> </think> tags before providing the answer.\nWrite your final answer within <answer> </answer> tags. Here is the question: {{ question }}{% if options %}\nOptions: \n\n{{ options }}{% endif %}\n\n
```

#### Prompt Template for Evaluation Multi-choice Questions

```
856
857
858
859
```

```
You should provide your thoughts within <think> </think> tags, then answer with just one of the options below within <answer> </answer> tags (For example, if the question is \n'Is the earth flat?\n A: Yes \nB: No', you should answer with <think>...</think> <answer>B: No</answer>). Here is the question: {{ question }}{% if options %}\n Options:\n\n{{ options }}{% endif %}\n\n
```

# Prompt Template for Evaluation Mathematical Questions

A conversation between User and Assistant. The user asks a question, and you as the assistant solves it. You should first think about the reasoning process in the mind and then provide the user with the answer. The reasoning process and answer are enclosed within <think> </think> and <answer> </answer> tags, respectively, i.e., <think> reasoning process here </think> <answer> the final answer as the option letter or the number depending on the question </answer> (For example, if the question is \n'Is the earth flat?\n A: Yes \nB: No', you should answer with <think> your reasoning </think> <answer>B: No</answer>. If the question is 'What is 1+1?', you should answer with <think> your reasoning </think> <answer>2 </answer>).\n\nHere is the question: {{ question }} {% if options %}\nOptions:\n\n{{ options }}{% endif %}\n\n

Table 6: Tasks for different evaluation settings. CC: CC BY-SA 4.0

Evaluation setting	Task name [license]	Shorthand	Data size
General-domain text-only	GSM8K main [MIT] (Cobbe et al., 2021)	GSM8K	1,319
General-domain text-only	MMLU-Pro [MIT] (Wang et al., 2024b)	MMLU-Pro	12,032
	MMMU (val) [CC]	MMMU	900
General-domain multimodal	MMMU-Pro [Apache-2.0] (Yue et al., 2024b)	MMMU-Pro	1,730
	MMStar [CC] (Chen et al., 2024b)	MMStar	1,500
(X-modality)	MathVista (testmini) [CC] (Lu et al., 2024)	MathVista	1,000
	MathVision [MIT] (Wang et al., 2024a)	MathVision	3,040
Specialized demain tout only	MedQA [MIT] (Jin et al., 2021)	MedQA	1273
Specialized-domain text-only	MedQA (4 options) [MIT] (Jin et al., 2021)	MedQA (4-ops)	1,273
(X-domain)	MMLU-Pro-Health [MIT] (Wang et al., 2024b)	MMLU-Pro-H	818
	MMMU-Health (Yue et al., 2024a)	MMMU-H	150
Ci-lid diltid-	MMMU-Pro-Health [CC] (Yue et al., 2024b)	MMMU-Pro-H	286
Specialized-domain multimoda	MedXpertQA-MM [MIT] (Chen et al., 2024b)	MXQ	2,000
(X-modality & X-domain)	OmniMedVQA [CC Zero] (Hu et al., 2024)	OMV	1,000
	NEJM Image Challenge	NEJM	947
	(New England Journal of Medicine, 2025)		

# E EVALUATION TASKS

Table 6 summarizes tasks used for different evaluation settings in our experiments: general-domain text-only, general-domain multimodal, specialized-domain text-only, and specialized-domain multimodal. We focus specifically on the medical domain as our representative specialized domain due to its significant practical importance and recent intensive research activities (Li et al., 2023; Zambrano Chaves et al., 2025; Zhang et al., 2025b; Luo et al., 2022; Nori et al., 2023; 2024; Codella et al., 2024; Poon et al., 2023; Xie et al., 2023; Ness et al., 2024). For OmniMedVQA, we sample 1000 from the full data for efficient evaluations.

#### F Previous SOTA Results

Table 7 lists details of the previous SOTA results for each task.

918 919

Table 7: Previous SOTA results. \* indicates our replicated results.

920
921
922
923
924
925

929 930 931

932 933

934

935

936

937

938

943

944

945

951 952 953

960

961

954

968

969 970

971

Task Previous SOTA Model Result 87.2 GSM8K MMOS-DeepSeekMath-7B (Chen et al., 2024c) MMLU-Pro Gemma-2-9B-it (Gemma Team et al., 2024) 52.1 MMMU-Pro MAmmoTH-VL2-7B (Jia et al., 2025) 40.7 MMMU (Val) Mulberry-7B (Yao et al., 2024) 55.0 MedOA (4-ops) HuatuoGPT-o1-7b (Chen et al., 2024a) 71.6\* MMLU-Pro-H HuatuoGPT-o1-7B (Chen et al., 2024a) 54.3\* MMMU-H GMAI-VL-RL (Su et al., 2025) 57.3 MedXpertQA-MM GMAI-VL-Rl (Su et al., 2025) 23.8

### CROSS-DISTRIBUTION/TASK GENERALIZATION OF SFT

We conduct a cross-distribution investigation where we fine-tune an instruction-tuned VLM, Qwen2.5-VL-7B-Instruct (Bai et al., 2025) using text-only MedQA (Jin et al., 2021), a specialized medical QA dataset. The training signal comprises detailed long-COT reasoning traces, distilled via rejection sampling (Huang et al., 2023; Zelikman et al., 2022) from QwQ-32B (Qwen Team, 2025). We then evaluate the model's generalization on an out-of-distribution task: MMLU-Pro-Health, the healthcare subset of MMLU-Pro (Wang et al., 2024b). The full training and evaluation details are provided in Sections 2.3 and 3. As shown in Table 8, all the SFT approaches consistently transfers the improvements from the source task (MedQA) to the target task (MMLU-Pro-Health), demonstrating strong cross-task generalization from text-only SFT.

Table 8: Comparing baseline and text-only SFT with and without CoT On MedQA task and evaluating on in & out of distribution tasks

Training: MedQA		Non-CoT		СоТ	
Eval: in & out of distribution	Modality	Baseline	SFT	Baseline	SFT
MedQA (In distribution) MMLU-Pro-H (Out of dist.)	Textual Textual	49.3 43.7	57.6 (+8.3) 47.2 (+3.5)	50.5 47.8	61.9 (+11.4) 54.2 (+6.4)

#### FORCED-EXITING TO MITIGATE ENDLESS THINKING IN LONG-COT SFT

While long-CoT SFT effectively learns transferrable reasoning patterns, such as self-reflection, verification, and correction (see qualitative analyses in Appendix O), we observe a recurring challenge: the model occasionally fails to terminate its responses. Specifically, the model continues generating tokens indefinitely without producing a stop signal. Such endless thinking occurs 13% of generations for MMLU-Pro-Health tasks and 32% for MMMU-Pro, as reported in (Table 9). Upon closer inspection, these failure cases are often characterized by verbose, repetitive output, where the model persistently attempts to "re-think" or "double-check", an artifact likely stemming from the reasoning mechanism introduced during long-CoT SFT (DeepSeek-AI et al., 2025).

To address this, we implement a forced-exiting mechanism inspired by the method introduced in Muennighoff et al. (2025). This involves appending a designated stop token '</think>' once the output sequence reaches a predefined length threshold. This soft intervention encourages the model to wrap up its reasoning process within a reasonable token budget. As shown in Table 9, applying forced-exiting effectively reduces endless thinking, thereby improving final task accuracy.

# COMPARISON OF RL AND SFT ON MEDQA DATA

We conduct a direct comparison between Rl, SFT and their combination with the same MedQA data. As shown in Table 10, pure RL performs worse than SFT and the hybrid SFT + RL performs the best.

Table 9: Forced-exiting mitigates endless thinking and improves final task accuracy from CoT SFT

Task	Before Forced-Exiting		After Forced-Exiting		
	% endless thinking	Accuracy	% endless thinking	Accuracy	
MMMU-Pro MMLU-Pro-Health	32.5% 13.4%	32.5 46	1.4% 0.1%	40.4 50.4	

Table 10: Comparison of performance from RL, SFT, and SFT + RL in both in-distribution (ind. text) and generalization settings, including out-of-distribution (ood. text) and cross-modality (X-modality). All models are trained on MedQA data.

Method	MedQA (ind. text)	MMLU-Pro-Health (ood. text)	MMMU-Pro-Health (X-modality)	Average Response Length (number of words)
baseline	50.5	47.8	34.3	111
SFT	61.9	54.2	39.2	950
RL	57.8	53.6	35.8	103
SFT + RL	64.9	55.8	39.7	1039

# J COMPARING SFT ON OPENTHOUGHTS AND ORZ MATH DATA

As in Table 11, we also experimented with using the Orz math data as well in the SFT stage by distilling CoT traces from QwQ-32B. We found that the X-Reasoner recipe with OpenThoughts SFT performs better than Orz math SFT. This suggests that we need more diverse general-domain training data than math in the SFT stage.

Table 11: Comparing SFT on OpenThoughts and Orz math data in the pipeline

Method	MMMU-Pro	MathVision
X-Reasoner (OpenThoughts SFT + Math RL)	42.5	29.4
Math SFT + Math RL	40.5	26.7

# K COMPARING MEDQA SFT + RL WITH X-REASONER-MED

As in Table 12, we also compare MedQA SFT + RL with X-REASONER-MED, which fine-tunes the general-domain X-REASONER using domain-specific data. X-REASONER-Med yields the strongest results, highlighting the benefit of starting from a generalist model and then applying domain-specific fine-tuning.

#### L CONTINUE TRAINING X-REASONER WITH MULTIMODAL DATA

As in Table 13, adding general-domain multimodal RL with ThinkLite data improves in-distribution performance (MathVista), but hurts generalization for the other tasks (MMMU-Pro, MMMU), highlighting the difficulty of curating broadly transferable multimodal data—a challenge we leave for future work. A recent follow-up (Wei et al., 2025) shows that with the right training regime, multimodal data can complement X-Reasoner's text-only base.

### M STANDARD DEVIATION

We report standard deviations for each experiment from the cross-modal evaluation (Figure 3) and cross-domain evaluation (Figure 4) in Table 14 and Table 15. We also report standard deviation for the RL training data experiments from Table 2 in Table 16.

Table 12: Comparing MedQA SFT + RL and X-REASONER-MED

Method	MedQA	MMLU-Pro-H	MMMU-Pro-H	MedXpertQA-MM
MedQA SFT + RL	64.9	55.8	39.7	24.4
X-REASONER-MED	66.7	57.9	40.0	25.9

Table 13: Continue training X-REASONER with multimodal data from ThinkLite Wang et al. (2025b)

Method	MMMU-Pro	MMMU	MathVista
X-REASONER (text-only) X-REASONER + ThinkLite RL (multimodal)	42.5	54.8	66.8
	39.9	52.7	70.7

Table 14: Standard Deviation for the Cross-Modality Evaluation in Figure 3 comparing X-REASONER and the baseline across 5 runs.

Method	GSM8k	MMLU-Pro	MMMU	MMMU-Pro	MMStar	MathVista (testmini)	MathVision
Baseline	0.22	0.29	0.61	0.39	0.47	0.10	0.59
X-REASONER	0.32	0.24	1.05	0.90	0.65	0.77	0.38

Table 15: Standard Deviation for evaluating X-REASONER, X-REASONER-MED and the baseline across 5 runs on medical benchmarks from Figure 4. MedQA (4): MedQA (4-ops), OMV: Omn-iMedVQA, MXQ: MedXpertQA-MM

Method	MedQA (4	4) MedQA	MMLU-P-	H MMMU-P-H	I MMMU-I	H OMV	NEJM	MXQ
Baseline	0.80	0.38	0.72	1.72	3.7	0.65	0.45	0.29
X-REASONER	0.89	0.87	0.61	1.49	2.71	0.96	0.81	0.48
X-REASONER-MED	0.85	0.46	0.78	0.65	4.76	0.96	0.42	0.88

Table 16: Standard Deviation for the results from the RI training data exploration in (Table 2)

Method	GSM8K	MMMU-Pro	MMLU-Pro-Health	MMMU-Pro-Health
Baseline	0.22	0.39	0.72	1.72
Math orz RL	0.49	0.78	1.13	2.10
MedQA RL	0.50	0.80	0.86	1.7
ThinkLite RL	0.51	0.30	0.76	1.24
OmniMedVQA RL	0.24	0.40	0.69	0.92

# N TRAINING DYNAMICS

Figure 5 shows the RL training dynamics when X-REASONER is being trained on Orz (Hu et al., 2025) and when X-REASONER-MED is being trained on MedQA (Jin et al., 2021), including training reward, policy gradient loss, mean advantage, mean training response length, training response clip ratio, validation accuracy.

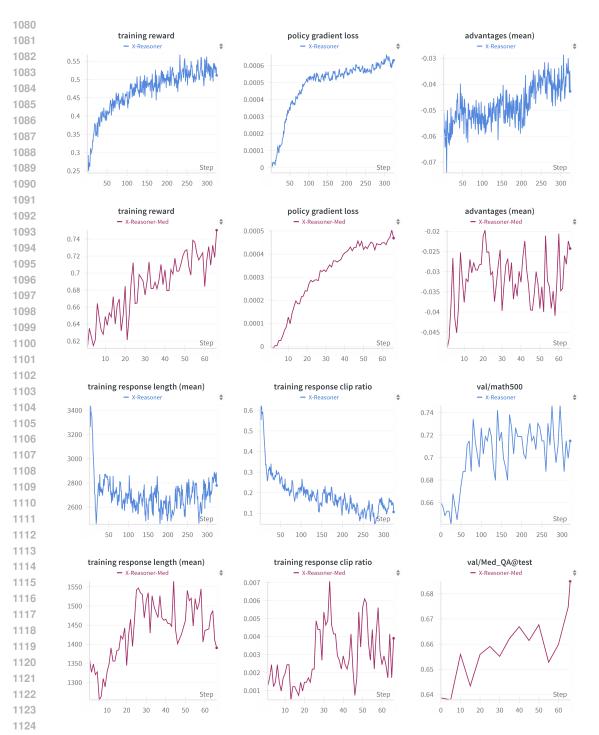


Figure 5: RL training dynamics of X-REASONER and X-REASONER-MED

# O QUALITATIVE ANALYSIS

112511261127

112811291130

1131

1132

1133

Table 17 shows some example reasoning output from X-REASONER as compared with the baseline. We can clearly see that X-REASONER is able to engage in more complex reasoning traces including detailed planning, verification ("wait). This complex reasoning patterns is successfully transferred to cross-modality setups where X-REASONER seamlessly integrates the vision information into the reasoning chain, and provides detailed step-by-step reasoning with verification for review/correc-

tion. In the example, X-REASONER provides a detailed plan to go over all the bar values whereas the baseline misses half of the bar values. X-REASONER is also able to correct its mistake in the reasoning chain. In the cross-modal cross-modality setting, X-REASONER connects the dots from both visual information and domain knowledge to the reasoning chain, and successfully identifies the patterns (white matter) from the histology slide and refers to its medical domain knowledge to connect it to progressive multifocal leukoencephalopathy.

Table 17: Reasoning output comparison between the baseline Qwen2.5-VL-7B-Instruct model and X-REASONER on an text-only question.

Question	The great dragon, Perg, satwithin a distance of 1000 feet. Polly could throw the gold javelinfor a distance of 400 feet, well within the reach of the dragon's flames. But when Polly held the sapphire gemstone, she could throw the javelin three times farther than when not holding the gemstone. If holding the gemstone, how far outside of the reach of the dragon's flames could Polly stand and still hit the dragon with the gold javelin? (from gsm8k main)
----------	--

#### Response

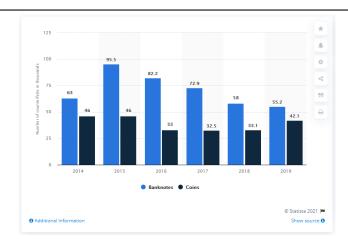
#### Baseline

<think> To solve this problem, we need to determine the maximum distance Polly can stand from the dragon and still hit it with the javelin when holding the sapphire gemstone. Here's the step-by-step reasoning: 1. When Polly is not holding the gemstone, she can throw the javelin for a distance of 400 feet. 2. When Polly holds the gemstone, she can throw the javelin three times farther than when not holding the gemstone. Therefore, the distance she can throw the javelin when holding the gemstone is \ ( 400 \times 3 = 1200 \) feet...\ ( 400 \times 3 = 1200 \) feet...\ ( 4nswer> 1200

#### X-REASONER

<think>Okay, let's see. First, let's break down the information. Without the gemstone, the javelin's distance is 400 feet. With the gemstone, it's three times that. So, 400 feet multiplied by 3 gives the new throwing distance. Let me calculate that: 400 \* 3 = 1200 feet... Wait, but is that correct? Let me check again. Wait, the problem says "how far outside of the reach of the dragon's flames could Polly stand and still hit the dragon with the gold javelin?" So, if the dragon's flames reach 1000 feet, then the maximum distance Polly can stand from the dragon's position and still hit it is 1200 feet. But the question is asking how far outside the dragon's flames she can stand. So, 1200 feet minus 1000 feet is 200 feet. Therefore, the answer should be 200 feet.

Table 18: Reasoning output comparison between the baseline <code>Qwen2.5-VL-7B-Instruct</code> model and X-REASONER on a multimodal question.



#### Question

How many bars have value below 40? (from MathVista)

# 1208 1209 1210

1211

1212

1213

1214

1215

1216

1217

1218

1219

1220

1223

1224

12251226

1227

1228

1229

1230

1231

12321233

120512061207

#### Baseline

<think>To determine how many bars have a value below 40, I'll examine each bar's value:

1. 2014: 63 (above 40)

Response

- 2. 2015: 95.5 (above 40)
- 3. 2016: 82.2 (above 40)
- 4. 2017: 72.9 (above 40)
- 5. 2018: 58 (above 40)
- 6. 2019: 55.2 (above 40)

None of the bars have a value below 40.</think><answer>0</answer>X

#### X-REASONER

<think> Okay, let's see. The question is asking how many bars have a value below 40. The image is a bar chart with two categories: Banknotes and Coins, and years from 2014 to 2019. Each year has two bars, one for each category. The values are given in the table, so we need to check each bar's value and count those below 40 thousand.

# First, let's go through each year:

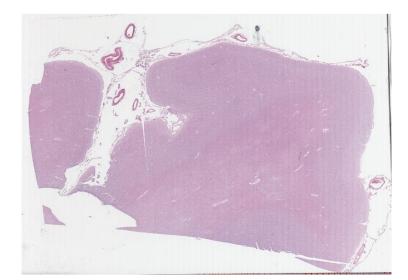
#### 2014:

- Banknotes: 63 thousand. That's above 40.
- Coins: 46 thousand. Also above 40.

Now, let's count the bars below 40:

- 2016: Coins (33)
- 2017: Coins (32.5)
- 2018: Coins (33.1)
- 2019: Coins (42.1) **Wait**, 42.1 is above 40. Wait, hold on. Wait, 2019's Coins is 42.1 thousand. 42.1 is above 40. So that's not below 40. So only the 2016 and 2017 Coins are below 40... Let's recast:
- 2014: Banknotes 63 (no), Coins 46 (no)  $\rightarrow$  0
- 2015: Banknotes 95.5 (no), Coins 46 (no)  $\rightarrow$  0
- 2016: Banknotes 82.2 (no), Coins 33 (yes)  $\rightarrow$  1
- 2017: Banknotes 72.9 (no), Coins 32.5 (yes)  $\rightarrow$  1
- 2018: Banknotes 58 (no), Coins 33.1 (yes)  $\rightarrow$  1
- 2019: Banknotes 55.2 (no), Coins 42.1 (no)  $\rightarrow$  0
- ... So total bars below 40: 3. Therefore, the answer is 3.
- </think>
- <answer>3</answer>✓

1239 1240 1241



#### Question

What is in the image? A. Progressive Multifocal Leukoencephalopathy (PML) B. Rabies C. West Nile Virus D. Herpes Simplex encephalitis E. Encephalitis Lethargica F. HIV encephalitis G. Lyme Disease H. Syphilis I. Meningitis J. Creutzfeldt-Jakob disease (from MMMU\_PRO HEALTH)

#### Response

#### Baseline

<think>The image appears to be a histological section, likely from a brain biopsy, given the presence of cellular structures and the context of the question. The pattern of the lesions and the cellular infiltration are characteristic of encephalitis. Herpes Simplex encephalitis (HSE) is a well-known cause of encephalitis, often presenting with a characteristic pattern of perivascular inflammation and necrosis, which can be seen in such images. The lesions in the image seem to have a focal nature, which is consistent with HSE. However, without further clinical information and a more detailed examination, a definitive diagnosis cannot be made.

Given the options, the most likely answer is:

D. Herpes Simplex encephalitis</think><answer>D. Herpes Simplex encephalitis</answer>

#### X-REASONER

<think> Okay, let's try to figure out this question. The image shows a histological section with some lesions. The question is about which neurological disease is depicted. Let me go through the options one by one. First, I remember that PML (Progressive Multifocal Leukoencephalopathy) is caused by the JC virus and typically affects the white matter of the brain, leading to lesions that can be seen on MRI as areas of low signal intensity on T2-weighted images. The histology might show demyelination and gliosis. The image here shows some irregular areas with a pinkish hue, which could be consistent with demyelination. But I need to check if the lesions are in the white matter. The image doesn't show the entire brain, but the lesions appear to be in the white matter, which is typical for PML. Rabies usually presents with encephalitis, but the histology isn't typically as specific as PML... Encephalitis Lethargica is an old disease, but its histology isn't as specific as PML.

Given the appearance of the lesions in the white matter, the pinkish areas, and the possibility of demyelination, PML seems the most likely. So the answer is A. </think> <answer>A</answer> ✓