# Synthetic vs. Authentic Data Training Effects on Multimodal Model Alignment in Medical VQA

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**Abstract**

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: To what extent does training multimodal foundation models on synthetic image-text pairs degrade alignment scores on out-of-distribution visual reasoning tasks relative to models trained on authentic. 15 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

## 1 Introduction

This paper examines: Beyond Accuracy: Evaluating Visual Grounding In Multimodal Medical Reasoning. Research question: To what extent does training multimodal foundation models on synthetic image-text pairs degrade alignment scores on out-of-distribution visual reasoning tasks relative to models trained on authentic data?.

## 2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.2/10.

## 3 Results

15 papers retrieved. 15 claims extracted; 1 independently verified. Quality review score: 4.2/10.

## 4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

## 5 Extracted Claims

| Claim | Verified | Confidence |
|---|---|---|
| RL(image) changes predictions only 39.8% of the time when images are shuffled, meaning 60.2% of answers ignore image con | × | 0.05 |
| The baseline model shows stronger visual dependence with an image sensitivity (IS) of 48.2%. | × | 0.13 |
| RL(text), trained without images, shows higher IS (50.0%). | × | 0.06 |
| RL(image) shows the lowest Visual Benefit Rate (VBR) (23.2%) across all models. | × | 0.05 |
| The VBR/VHR ratio for RL(image) is 1.74, compared to 1.91 for baseline. | × | 0.02 |
| PathVQA shows negative visual reliance with RL(text) achieving VRS = -0.09. | × | 0.12 |
| RL(text) trained without any images achieves 65% accuracy with shuffled images and 56% accuracy with correct images on P | × | 0.10 |
| Models can improve benchmark accuracy primarily through textual priors while simultaneously weakening the causal depende | × | 0.05 |
| Models exploit text-based shortcuts in benchmarks to maximize their accuracy rewards. | × | 0.09 |
| Three Qwen2.5-VL-7B variants are evaluated: Baseline, RL(text), and RL(image). | × | 0.03 |
| Baseline is pretrained without medical fine-tuning. | × | 0.08 |
| RL(text) is trained via RLVR on text-only medical QA (m23k, 23K examples). | × | 0.06 |
| RL(image) is trained via RLVR on image-text medical QA (PMC-VQA). | × | 0.14 |
| Publicly released checkpoints from Huang et al. (2025b) are used with deterministic decoding (temperature=0). | × | 0.01 |
| Four medical VQA benchmarks are evaluated: PathVQA, PMC-VQA, SLAKE, and VQA-RAD. | ✓ | 0.24 |

## References


- http://arxiv.org/abs/2312.14232v3

- http://arxiv.org/abs/2408.07303v2
- http://arxiv.org/abs/2603.03437v1