

Laterality Failure in Vision-Language Models on Surface Clinical Photographs: A Pilot Safety Study

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Abstract

Anatomical laterality is a basic but safety-critical clinical output. We test whether medical and general-purpose vision-language models (VLMs) can reliably assign patient left-right laterality from RGB photographs with clear unilateral landmarks. In a 9-model pilot, aggregate scorable accuracy was 42.6%, with some models as low as 12.5%. Motivated by prior work suggesting that explicit verbal reasoning can interfere with visual-spatial judgments, we compared reasoning-enforced and direct prompts; effects were inconsistent, producing both improvements and degradations rather than a reliable repair. We then evaluated 30 contemporary VLMs on a controlled laterality stress test with transformations and abstention controls. Models separated into recurrent failure modes, including side-label bias, mixed/near-chance behavior, over-abstention, and output-format failure. These patterns are not explained by prompt sensitivity alone and instead indicate unstable spatial grounding. Laterality should therefore be treated as a distinct safety failure mode requiring structural, not merely linguistic, safeguards in clinical VLM applications.

Keywords: laterality, vision-language models, spatial reasoning, reference-frame failure, clinical photography, wound imaging, patient safety

1. Introduction

Vision-language models (VLMs) are increasingly used for wound and surface-image interpretation, including WoundCareVQA (Yim et al., 2025). Yet strong multimodal benchmark performance can mask weaknesses in low-level visual grounding: VLMs fail simple visual-spatial tasks requiring precise localization (Rahmanzadehgervi et al., 2024), can produce plausible but ungrounded explanations (Asadi et al., 2026), and remain vulnerable to frame-of-reference ambiguity (Zhang et al., 2024).

Anatomical laterality places these concerns in a safety-critical clinical setting. Relative-position failures have been documented in standardized medical imaging (Wolf et al., 2025), but surface clinical photography adds a distinct challenge: mirroring, rotation, and view-point shifts can preserve visible landmarks while destabilizing the mapping from image coordinates to the patient’s left-right frame. Because incorrect laterality can propagate into documentation and downstream decision support, we test whether current VLMs can assign patient-side laterality from visually obvious RGB photographs, and whether direct prompts repair failures seen with reasoning-enforced prompts.

2. Methods

We used a two-stage design: an 8-image, 9 models pilot using a reasoning-enforced prompt, followed by a 30-model stress test using prompt variation, mirroring, repeated querying, rotation, alternate views, and abstention controls.

The final image set contained 17 RGB images: 10 unilateral anatomical images with left/right ground truth, two non-anatomical controls, and five bilateral anatomical controls for which laterality should not be assigned. The unilateral set included peri-ocular, forehead, foot, and lower-extremity views, including a controlled right-leg trio with original, 90° rotated, and medial-side views. Images were drawn from publicly available wound-care imagery and non-identifiable author-supplied examples; labels and metadata were removed where possible.

Prompts allowed `unable_to_determine` (UTD). The primary outcome was exact-match unilateral laterality accuracy. Secondary measures included label distribution, control UTD accuracy, and qualitative failure mode classification. Failure modes were assigned from observed response distributions: side-label bias denotes asymmetric left/right output, over-abstention denotes high UTD on unilateral images, and forced laterality denotes low UTD on controls.

3. Results

Initial cross-model pilot. In the initial 8-image pilot (Supplementary Material), aggregate accuracy across nine VLMs ranged between 12.5% to 42.6%. Comparing a reasoning-enforced prompt with a more direct prompt did not yield a consistent repair: some model-image pairs improved, whereas others deteriorated.

30-model stress test. In the expanded stress test, laterality failure did not appear as a single error type. Across 30 VLMs, unilateral accuracy ranged from 0.0% to 56.4%, despite visually obvious landmarks. Observed label distributions deviated from the ground-truth prior (29.4%/29.4%/41.2%), indicating systematic bias rather than random error. GPT-5.2 achieved the highest unilateral accuracy (56.4%) but still showed mixed/near-chance laterality, with observed left, right, and UTD rates of 33.1%, 33.3%, and 28.9%, respectively. Claude Opus 4.6 showed a similar mixed pattern (55.3%). GPT-5.4-mini also remained in the mixed/near-chance regime, with 48.8% unilateral accuracy (Supplementary Material - Table 3).

Failure modes. Models segregated into recurrent behavioral patterns. Several models showed strong side-label bias: `pixtral-12b` and `mobilevlm-3b` produced left labels in 68.5% and 66.2% of responses, respectively, while `google/gemma-3-4b` produced right labels in 72.3%. Other models were mixed or near-chance, including GPT-5.2, Claude Opus 4.6, GPT-5.4-mini, `qwen/qwen2.5-vl-7b`, and `mistralai/ministral-3-3b`. A third group over-abstained with high UTD rates, including `google/gemma-3-27b` (78.7%), `google/gemma-4-e4b` (95.2%), and `kimi-vl-a3b-thinking-2506` (95.0%). Several models failed primarily through invalid or empty outputs, including `google/mixtral.ai_vision_128k.7b`, which produced invalid outputs in 100.0% of trials.

Control behavior. Control UTD accuracy varied widely, from 0.0% to 99.2%. Some models abstained nearly perfectly on controls, such as `grok-4-fast-non-reasoning` (99.2%) and `llava-1.6-mistral-7b` (97.9%), but did so while severely over-abstaining on unilateral

images. Conversely, MedGemma 4B produced right labels in 67.1% of outputs and achieved only 33.6% control UTD accuracy, consistent with forced laterality rather than calibrated abstention. These results argue against a single explanation such as random guessing; VLMs fail through heterogeneous combinations of side bias, instability, over-abstention, and output-format failure.

Model	Uni Acc	Left	Right	UTD	UTD Acc	Failure mode
GPT-5.2	56.4	33.1	33.3	28.9	70.0	Mixed/near-chance
Claude Opus 4.6	55.3	23.3	43.3	30.2	73.0	Mixed/near-chance
Pixtral-12B	49.2	68.5	12.7	18.8	95.8	Left-label bias
Gemma-3-4B	48.8	2.6	72.3	25.1	58.1	Right-label bias
MedGemma 4B	49.0	16.7	67.1	16.2	33.6	Forced right laterality
MedGemma3-thinking	27.5	12.1	24.1	63.8	91.5	UTD over-abstention
LLaVA-1.6-Mistral-7B	12.6	17.8	5.8	76.0	97.9	UTD over-abstention
Mixtral Vision 128K 7B	0.0	0.0	0.0	0.0	0.0	Format/empty failure

Table 1: Representative models spanning observed laterality failure modes. Metrics include unilateral accuracy (Uni Acc), prediction distribution, and control abstention accuracy (UTD Acc). Full results are provided in Supplementary Table 3.

4. Discussion

This stress test suggests that anatomical laterality is a distinct failure mode for medical and general-purpose VLMs rather than a minor prompt artifact. Across 30 models, failures clustered into distinct patterns: side-label biases, mixed/near-chance laterality, UTD over-abstention, forced laterality on controls, and output failure. These mutually different behaviors imply that current VLMs do not share a stable mechanism for mapping visible anatomical landmarks into patient-centered reference frames.

The control images provide further insights. Some models abstained appropriately on non-lateralizable inputs, whereas others forced laterality labels or failed to produce valid outputs. Thus, laterality failure is not simply indiscriminate guessing. Instead, once an image is determined to be anatomically relevant, models may alternate between biased side priors, unstable spatial mappings, and overly conservative uncertainty behavior.

These findings matter because laterality errors can propagate into documentation, longitudinal wound tracking, and downstream decision support. Although this study is small, the controlled transformations suggest that laterality can function as a useful stress test for spatial grounding in VLMs. Laterality may require structural safeguards rather than prompt engineering or routine finetuning.

5. Conclusion

Medical VLMs can recognize anatomy yet still fail the safety-critical task of assigning the patient’s correct left-right side. Across 30 models, laterality failure appeared as a spectrum of spatial grounding breakdowns, including side bias, near-chance instability, over-abstention, and output failure. Laterality should therefore be treated as a dedicated safety stress test for VLMs and may require structural safeguards before clinical deployment.

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Supplementary Material

Images were deliberately selected to include clear medial–lateral anatomical landmarks that allow easy laterality determination by lay observers. No images were intrinsically ambiguous, occluded, or low quality.

Labels, metadata, and bilateral context were removed to isolate laterality inference from external cues, reflecting common wound-care photography practices.

Each image was also evaluated in a horizontally mirrored form. If laterality reasoning is truly landmark-based, predicted laterality should reverse when the image is flipped.

Laterality for all images is visually obvious to human observers without medical training.



Prompt 1: You are an expert clinician specializing in human anatomy. Determine the laterality of the human part shown in the photo. Explain your reasoning.

This prompt reflects a commonly used reasoning-based baseline and was used to generate the cross-model comparison results shown in Table 1.

Table 1

VLM	1	2	3	4a	4b	5	6	7
ChatGPT 5.2	R	L	L	R	R	L	L	L
Gemini 3 Pro	R	R	L	L	L	R	L	R
Grok 4	R	R	L	L	L	R	R	L
Claude 4.5 Sonnet	R	R	L	R	R	R	R	R
Meta: Llama 4 Maverick	R	R	L	R	R	R	L	R
Kimi 2.5 Thinking	R	R	L	L	L	L	L	R
Perplexity	R	L	R	L	L	R	L	N/A
DoxGPT (Professional)	L	R	R	L	R	L	R	R
OpenEvidence (Professional)	L	R	L	N/A	N/A	R	L	L
Ground Truth (based on visible landmarks)	L	L	R	R	R	R	L	R

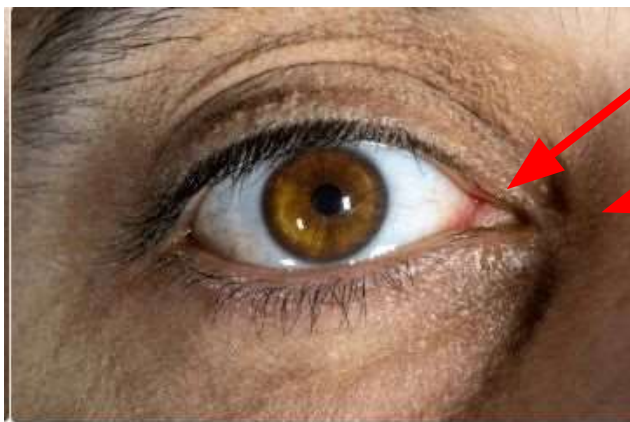
R = Right, L = Left, U = Uncertain, N/A = Answer not available/Outside of scope

Correct

Inconsistent

Errors in this table occur despite often correct identification of the anatomical structure itself.

Example Incorrect Reasoning



1. Identify the medial canthus: The medial canthus is the area where the eyelids meet near the nose. It is characterized by a small, fleshy prominence called the lacrimal caruncle. In the given image, the lacrimal caruncle is visible on the right side of the image.
2. Determine the orientation: Since the lacrimal caruncle is on the right side of the image, this indicates that the nasal or medial aspect of the eye is oriented towards the right side of the image.
3. Relate to the subject's anatomy: When viewing a face directly, the left side of the face appears on the viewer's right, and the right side appears on the viewer's left. **Therefore, if the medial canthus is on the right side of the image, it corresponds to the subject's left eye.**
4. Conclusion: Based on the location of the medial canthus and lacrimal caruncle on the right side of the image, the eye depicted is the left eye of the subject

The model identifies the medial canthus but mis-maps image orientation to the patient's left–right frame.



Prompt 1 (Reasoning-Enforced)

*“You are an expert clinician specializing in human anatomy.
Determine the laterality of the human part shown in the photo.
Provide a brief landmark-based justification.”*

Prompt 2 (Direct)

*“You are an expert clinician specializing in human anatomy.
Determine the laterality of the human part shown in the photo.”*

Research in cognitive science shows that people usually understand space through visual perception rather than by following strict rules. When humans are asked to explain spatial judgments using words, mistakes can occur, especially for left–right or orientation decisions. This is because verbal reasoning can interfere with how the brain naturally represents space visually (Ullman, 1984; Tversky, 2005).

Recent studies show that similar issues appear in vision-language models. Benchmark evaluations demonstrate that these models often struggle with spatial relationships when images are ambiguous and may confuse different frames of reference, such as the viewer’s perspective versus the object’s perspective (Zhang et al., 2024). This problem is especially clear for left–right judgments. In medical imaging tasks, models frequently make laterality errors even when the visual information is clear, indicating a systematic weakness in relative positioning (Wolf et al., 2025). Other research suggests that forcing models to generate step-by-step explanations does not always improve performance and can sometimes increase errors when the explanation does not reflect how the model actually made its decision (Goyal et al., 2019; Chen et al., 2024).

Experimental Question: Does explicit verbal reasoning improve or degrade laterality determination when clear anatomical landmarks are present?

Table 2

LLM Prompt 1 ->. 2	1	2	3	4a	4b	5	6	7
ChatGPT 5.2	R -> L	L->R	L	R	R	L	L	L
Gemini 3 Pro	R -> L	R -> L	L -> R	L	L	R -> L	L	R
Grok 4	R	R	L	L->R	L	R -> L	R	L -> R
Claude 4.5 Sonnet	R	R -> L	L -> R	R	R -> L	R	R	R
Meta: Llama 4 Maverick (Scout)	R -> L	R	L -> R	R -> LA	R -> RA	R	L	R
Kimi 2.5 Thinking	R	R -> L	L -> R	L -> R	L	L -> R	L	R
Perplexity	R	L	R	L	L	R	L	N/A
DoxGPT (Professional)	L	R -> L	R -> L	L -> R	R -> L	L	R	R -> L
OpenEvidence (Professional)	L -> R	R->L	L -> R	N/A	N/A	R	L	L
Ground Truth	L	L	R	R	R	R	L	R

R = Right, L = Left, LA = Left Arm, RA = Right arm, N/A = Answer not available/Outside of scope

Deterioration **Improvement** **Correct** **Inconsistent**

Prohibit explicit reasoning did **not** consistently improve laterality accuracy and, in some cases, introduced additional spatial reference-frame errors, despite the presence of visually obvious anatomical landmarks.

AI Struggles to Consistently Tell Left from Right

Flip-flopping left/right calls reveal uncertainty near decision thresholds in a subset of cases (GPT 5.2 using default settings, 20 trials each).

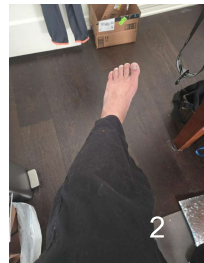


Image	Correct	Binomial p-value ($H_0: p = 0.5$)	Two-proportion test
1	100%	$p < 0.001$ (perfect accuracy)	Stable under mirroring.
2 (Mirror of 1)	100%	$p < 0.001$ (perfect accuracy)	
3	55%	ns = random	Mirroring significantly changed laterality performance ($p \approx 0.008$)
4 (Mirror of 3)	15%	$p = 0.003$ (systematic error, non-random)	
5	85%	$p = 0.003$ (non-random)	No significant difference due to mirroring. ($p=0.43$)
6 (Mirror of 5)	75%	$p = 0.04$ (reduced but still above chance accuracy)	

Statistical significance was evaluated using an exact binomial test assuming $p = 0.5$ (random guessing). This tests whether observed laterality accuracy for each image differs from chance. Both high and low accuracies were interpreted as evidence of non-random behavior.

We tested whether laterality accuracy differed between original and mirrored images using a two-proportion test on correctness rates.

Benchmark Image Set



Controls

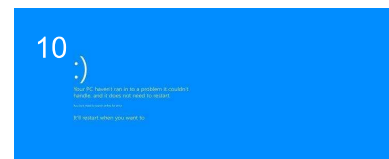
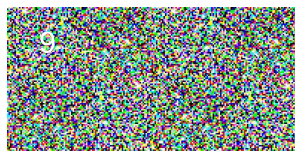
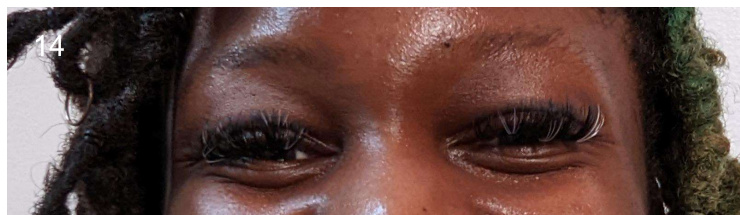


Table 3

Model	Obs Left %	Obs Right %	Obs UTD %	Invalid %	Uni Acc %	Ctl UTD Acc %	Failure Mode
gpt-5.2-chat-latest	33.1%	33.3%	28.9%	4.7%	56.4%	70.0%	Mixed/near-chance laterality
claude-opus-4-6	23.3%	43.3%	30.2%	2.8%	55.3%	73.0%	Mixed/near-chance laterality
lumimaid_vision-v0.2-12b-pixtral	63.4%	12.0%	24.5%	0.1%	49.2%	55.0%	Left-label bias
pixtral-12b	68.5%	12.7%	18.8%	0.1%	49.2%	95.8%	Left-label bias
unsloth/medgemma-4b-it	16.7%	67.1%	16.2%	0.0%	49.0%	33.6%	Right-label bias
gpt-5.4-mini-2026-03-17	39.2%	24.8%	36.1%	0.0%	48.8%	75.6%	Mixed/near-chance laterality
google/gemma-3-4b	2.6%	72.3%	25.1%	0.0%	48.8%	58.1%	Right-label bias
mimo-v2-omni	25.5%	35.2%	32.8%	6.4%	47.5%	76.2%	Right-label bias
gemini-3-flash	18.8%	39.3%	38.9%	2.9%	45.7%	90.8%	Right-label bias
microsoft.phi-4-reasoning-vision-15b	33.0%	18.4%	48.6%	0.0%	43.1%	96.5%	UTD over-abstention
qwen/qwen2.5-vl-7b	33.2%	33.4%	33.3%	0.1%	41.6%	56.7%	Mixed/near-chance laterality
mistralai/ministral-3-3b	35.5%	32.5%	29.0%	2.9%	38.9%	45.2%	Mixed/near-chance laterality
qwen/qwen3-vl-30b	40.2%	12.7%	47.1%	0.0%	37.9%	74.4%	Left-label bias
qwen/qwen3-vl-4b	33.5%	20.1%	46.4%	0.0%	37.5%	74.8%	Mixed/near-chance laterality
mobilevlm-3b	66.2%	6.6%	7.0%	20.2%	35.9%	7.4%	Left-label bias
llava-v1.5-7b	56.5%	7.8%	17.3%	18.3%	31.1%	17.1%	Left-label bias
medgemma3-thinking	12.1%	24.1%	63.8%	0.0%	27.5%	91.5%	UTD over-abstention
granite-vision-3.2-2b	26.2%	11.4%	49.9%	12.5%	27.4%	76.4%	UTD over-abstention
llava-v1.6-34b	31.3%	19.4%	32.2%	17.1%	26.1%	47.0%	Left-label bias
mistralai/devstral-small-2-2512	10.2%	19.9%	69.9%	0.0%	21.9%	93.9%	UTD over-abstention
smolvlm2-2.2b-instruct	22.7%	10.0%	62.6%	4.6%	18.1%	69.9%	UTD over-abstention
google/gemma-3-27b	12.1%	9.3%	78.7%	0.0%	13.2%	85.6%	Severe UTD over-abstention
llava-1.6-mistral-7b	17.8%	5.8%	76.0%	0.3%	12.6%	97.9%	Severe UTD over-abstention
grok-4-fast-non-reasoning	7.4%	3.2%	65.9%	23.5%	10.4%	99.2%	UTD over-abstention
qwen/qwen3.6-35b-a3b	3.5%	2.6%	12.5%	81.4%	5.9%	30.2%	Format/empty failure
google/gemma-4-e4b	1.8%	3.0%	95.2%	0.0%	3.4%	97.9%	Severe UTD over-abstention
kimi-vl-a3b-thinking-2506	0.9%	4.1%	95.0%	0.0%	2.6%	96.1%	UTD over-abstention
mistralai/ministral-3-14b-reasoning	0.2%	0.6%	36.4%	62.7%	0.6%	46.8%	Format/empty failure
google/zai-org/glm-4.6v-flash	1.4%	0.8%	11.2%	86.6%	0.6%	21.8%	Format/empty failure
google/mixtral_ai_vision_128k_7b	0.0%	0.0%	0.0%	100.0%	0.0%	0.0%	Format/empty failure
Ground Truth	29.4%	29.4%	41.2%				

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<https://coder231212.github.io/AI-Laterality-Challenge/>