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# Are Large Vision Language Models Truly Grounded in Medical Images? Evidence from Italian Clinical Visual Question Answering

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## Abstract

Large vision language models (VLMs) have achieved impressive performance on medical visual question answering benchmarks, yet their reliance on visual information remains unclear. We investigate whether frontier VLMs demonstrate genuine visual grounding when answering Italian medical questions by testing four state-of-the-art models: Claude Sonnet 4.5, GPT-4o, GPT-5-mini, and Gemini 2.0 flash exp. Using 60 questions from the EuropeMedQA Italian dataset that explicitly require image interpretation, we substitute correct medical images with blank placeholders to test whether models truly integrate visual and textual information. Our results reveal striking variability in visual dependency: GPT-4o shows the strongest visual grounding with a 27.9pp accuracy drop (83.2% [74.6%, 91.7%] to 55.3% [44.1%, 66.6%]), while GPT-5-mini, Gemini, and Claude maintain high accuracy with modest drops of 8.5pp, 2.4pp, and 5.6pp respectively. Analysis of model-generated reasoning reveals confident explanations for fabricated visual interpretations across all models, suggesting varying degrees of reliance on textual shortcuts versus genuine visual analysis. These findings highlight critical differences in model robustness and the need for rigorous evaluation before clinical deployment.

## 1 Introduction

Recent advances in large vision language models have led to remarkable performance on medical benchmarks, with systems approaching or exceeding human expert performance on visual question answering tasks [1]. However, high benchmark scores may mask fundamental limitations in how these models process and integrate visual information with clinical reasoning [2, 3]. The medical AI community faces a critical question: do these models succeed through genuine multimodal understanding, or do they exploit spurious correlations and textual shortcuts? This question is particularly important for healthcare applications, where erroneous diagnoses based on faulty visual reasoning could have serious consequences. Building on recent work that exposed hidden fragilities in frontier models through systematic stress testing [1], we investigate visual grounding in medical question answering using Italian clinical cases. Our approach differs from prior work by (1) comparing multiple frontier VLMs, (2) focusing on a non-English medical dataset, and (3) employing a targeted visual substitution methodology that tests whether models truly rely on image content when rendering diagnostic judgments.

## 1.1 Contributions

- We present the first systematic comparison of four frontier VLMs (Claude Sonnet 4.5, GPT-4o, GPT-5-mini, and Gemini 2.0 flash exp - referred to as Gemini 2.0) on 60 Italian medical visual question answering cases requiring explicit image interpretation.
- We introduce a visual substitution methodology revealing striking differences in visual dependency across models, with accuracy drops ranging from 2.4pp to 27.9pp.
- We provide empirical evidence that most current VLMs maintain surprisingly high accuracy with incorrect images, suggesting varying reliance on textual cues rather than robust visual understanding.

## 2 Related Work

**Medical Visual Question Answering.** Medical VQA benchmarks such as VQA-RAD [4], PMC-VQA [5], and PathVQA [6] have driven progress in multimodal medical AI. However, recent work has questioned whether these benchmarks truly measure medical understanding or merely test-taking ability [1].

**Robustness and Shortcut Learning.** The ML community has documented extensive shortcut learning in vision-language models [7], where models exploit spurious correlations rather than learning robust features. In medical imaging, this manifests as reliance on metadata, dataset artifacts, or textual priors rather than genuine visual analysis [8].

**Stress Testing Large Models.** Recent work by Microsoft Research [1] introduced systematic stress tests revealing that frontier models often succeed for the wrong reasons, maintaining high accuracy even when critical inputs are removed or perturbed. Our work extends this methodology to Italian medical cases with comparative analysis across multiple VLMs.

## 3 Methodology

### 3.1 Dataset

We utilized the EuropeMedQA dataset [9], specifically the Italian State Exam for Medical Doctors (SSM) subset. From this collection, we manually curated 60 multiple-choice questions that explicitly require visual interpretation for correct diagnosis. Questions span cardiology (27%), orthopedics (12%), dermatology (13%), neurology (10%), gastroenterology and pulmonology (8% each), and other specialties including preventive medicine/epidemiology (5%), oncology (3%), and hematology, ophthalmology, and trauma surgery (2% each).

Each question includes a clinical vignette in Italian, a medical image (X-ray, CT scan, dermatological photo, ECG, etc.), five answer options (A-E), and the ground truth correct answer.

### 3.2 Experimental Design

We conducted a visual substitution experiment across four frontier VLMs: Claude Sonnet 4.5, GPT-4o, GPT-5-mini, and Gemini 2.0. For each model:

**Original Condition.** The model answered questions with correct medical images attached, generating both an answer selection and detailed reasoning.

**Substitution Condition.** We replaced each medical image with an identical blank placeholder while keeping question text and answer options unchanged. Models truly dependent on visual information should show decreased accuracy when diagnostically relevant images are replaced.

We prompted all models to provide both answer selection and detailed step-by-step reasoning using chain-of-thought prompting, following [1]. This allowed analysis of whether explanations reflected actual image content or hallucinated features.

### 3.3 Evaluation Metrics

We measured: (1) **Accuracy** in original vs. substitution conditions, (2) **Accuracy drop** as the primary indicator of visual dependency, and (3) **Reasoning quality** through manual analysis of generated explanations for hallucinations and misaligned visual descriptions.

## 4 Results

### 4.1 Quantitative Analysis

Table 1 summarizes our comparative findings across 10 repetitions per model. The models show striking variability in visual dependency:

**GPT-4o** demonstrates the strongest visual grounding with 83.2% accuracy (95% CI: [74.6%, 91.7%]) on real images dropping to 55.3% (95% CI: [44.1%, 66.6%]) with fake images (27.9pp decrease), suggesting substantial reliance on actual visual content for diagnostic reasoning.

**GPT-5-mini** achieves the highest baseline accuracy (88.0%, 95% CI: [81.3%, 94.7%]) but maintains 79.5% (95% CI: [69.7%, 89.3%]) with substituted images (8.5pp drop), indicating improved textual reasoning but potentially less visual dependency than GPT-4o.

**Gemini 2.0** shows 83.7% accuracy (95% CI: [74.3%, 93.0%]) with real images and 81.3% (95% CI: [71.7%, 91.0%]) with fake images (2.4pp drop), demonstrating the smallest performance degradation and suggesting strong reliance on textual cues.

**Claude Sonnet 4.5** achieves 82.8% (95% CI: [73.7%, 91.9%]) with real images and 77.2% (95% CI: [66.6%, 87.7%]) with fake images (5.6pp drop), showing moderate visual dependency between GPT-4o and the other models.

Table 1: Comparative performance of four frontier VLMs on Italian medical VQA with correct vs. substituted images (N=60 questions, 10 repetitions per model).

Model	Real Images	Fake Images	Drop
GPT-5-mini	88.0% [81.3, 94.7]	79.5% [69.7, 89.3]	8.5pp
Gemini 2.0	83.7% [74.3, 93.0]	81.3% [71.7, 91.0]	2.4pp
GPT-4o	83.2% [74.6, 91.7]	55.3% [44.1, 66.6]	<b>27.9pp</b>
Claude Sonnet 4.5	82.8% [73.7, 91.9]	77.2% [66.6, 87.7]	5.6pp

For context, human performance on the Italian State Exam in 2024 averaged 74.8%, with 9.6% of test takers scoring above 95.6% [10]. All models exceed average human performance with real images, but GPT-4o drops significantly below the human average when images are removed, largely because it refuses to answer the question, while the other models maintain superhuman accuracy even without visual information.

### 4.2 Qualitative Analysis of Reasoning

We identified three recurring patterns in model-generated explanations across all four VLMs:

**Hallucinated Visual Features.** Models frequently described specific visual findings absent from images. For example, when shown a blank placeholder for an anterior MI question (correct answer: C describing precordial ST elevation), multiple models confidently described fabricated ECG findings matching various answer options, despite viewing diagnostically empty images.

**Answer-Driven Reasoning.** Models appeared to select answers first (possibly from textual cues), then construct visual justifications post-hoc. This was evident when identical questions with different images received the same answers but with contradictory visual descriptions supporting that answer.

**Overconfident but Wrong.** Even when answers changed due to image substitution, models provided equally confident and detailed reasoning in both conditions, suggesting inability to reliably distinguish between cases with strong versus weak or contradictory visual evidence.

## 5 Discussion

Our comparative findings reveal substantial heterogeneity in visual grounding across frontier VLMs. GPT-4o’s 27.9pp accuracy drop represents the strongest evidence of genuine visual dependency, suggesting this model more robustly integrates image content into diagnostic reasoning. In contrast, GPT-5-mini, Gemini, and Claude maintain high accuracy with minimal drops (2.4pp-8.5pp), indicating these models can achieve correct diagnoses primarily through textual inference.

These results have important implications for understanding model architectures and training objectives. GPT-4o’s greater visual dependency may reflect architectural choices prioritizing multimodal integration, while newer models (GPT-5-mini, Gemini 2.0) appear optimized for robust textual reasoning that can compensate for degraded visual inputs. Whether this represents progress or regression depends on the deployment context.

### 5.1 Trade-offs Between Visual Dependency and Accuracy

Our results reveal a complex relationship between visual grounding and overall performance. GPT-5-mini achieves the highest baseline accuracy (88.0%) with the narrowest confidence interval (95% CI: [81.3%, 94.7%]) while showing less visual dependency than GPT-4o, raising questions about the optimal balance. Models with strong textual reasoning may be more robust to image quality issues in real-world clinical settings, but risk missing critical visual findings or generating plausible but incorrect diagnoses when visual and textual cues conflict.

### 5.2 Implications for Medical AI

These findings have important implications for deploying VLMs in clinical settings:

**Model Selection.** Applications requiring strict visual interpretation should favor models like GPT-4o with demonstrated visual dependency, while decision support systems synthesizing multimodal information might benefit from models with stronger textual reasoning.

**Benchmark Inflation.** Standard accuracy metrics overestimate real-world readiness by failing to distinguish genuine multimodal reasoning from textual shortcuts. GPT-4o-mini and Gemini could achieve >75% accuracy on many medical VQA benchmarks without functional vision.

**Safety Concerns.** All models generated confident but incorrect visual descriptions, potentially misleading clinicians. This risk spans the performance spectrum and can obscure critical diagnostic errors. The EU AI Act classifies such systems as high-risk, requiring measures to counter automation bias and ensure human oversight [11].

**Evaluation Needs.** Stress testing should become standard before clinical deployment, with explicit measurement of visual dependency alongside conventional accuracy metrics.

### 5.3 Limitations

Our study has several limitations. First, we evaluated only four models on 60 questions from Italian medical exams. Second, our blank image substitution represents a coarse test of visual dependency—more refined adversarial attacks [12] substituting images depicting alternative pathologies would provide stronger evidence of whether models detect image-text misalignment. Third, we did not perform membership inference attacks [13, 14] to determine whether EuropeMedQA was in training data. High accuracy without images may reflect robust textual reasoning or dataset memorization; membership inference would help distinguish these explanations. Finally, findings may vary across languages and medical specialties.

## 6 Conclusion

We investigated visual grounding in frontier VLMs through systematic image substitution on Italian medical VQA cases. Our results reveal striking heterogeneity: GPT-4o shows strong visual dependency (27.9pp drop), while GPT-5-mini, Gemini, and Claude maintain high accuracy with minimal drops (2.4–8.5pp). All models generate confident explanations for fabricated visual features, raising safety concerns regardless of baseline performance.

These findings suggest current benchmarks overestimate visual understanding in medical VLMs and highlight the need for model-specific evaluation of visual dependency. Before clinical deployment, we must develop rigorous testing methodologies that distinguish genuine multimodal reasoning from textual shortcuts and memorization. Future work should extend this analysis to larger datasets, additional stress testing methodologies, and investigation of the architectural factors underlying these differences in visual grounding.

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## A Detailed Case Studies of Model Confabulation

### A.1 GPT-5-mini

Figure 1 presents two detailed case studies demonstrating systematic visual fabrication behavior in GPT-5 mini when presented with blank images instead of authentic medical imaging, despite reaching correct diagnostic conclusions.

**GPT-5-mini: Fabricates Visual Details Even When Correct**

**Case 1: Chest X-ray - ECG Electrodes vs Pathology**

Question: "Un paziente di 60 anni deve essere sottoposto a colectomia. In regime di preoperatorio ha eseguito un controllo radiologico del torace. L'immagine radiologica mostrata in figura è in prima istanza compatibile con?" (Bye preop chest X-ray - what is seen?)

✓ With Image



What is the image compatible with?

- A. Malignant tubercolosi
- B. Plurimetaстic metastases
- C. Multifocal pneumonia
- D. Atelectasis
- E. ECG electrodes ✓

GPT-5-mini: "E. ECG electrodes"

Correctly identifies. Round opacities, uniform size/density, well-demarcated, peripheral/superficial location (some outside lung fields) → typical appearance of radiopaque ECG discs

✓ Accurate diagnosis

△ Without Image - Fabricates

No Image

What is the image compatible with?

- A. Malignant tubercolosi
- B. Plurimetaстic metastases
- C. Multifocal pneumonia
- D. Atelectasis
- E. ECG electrodes ✓

GPT-5-mini: "E. ECG electrodes"

Claims: Round, well-demarcated opacities in superficial/location, regularly distributed, not intraparenchymal → typical ECG electrode pattern (ALL FABRICATED)

! Correct but fabricated

**Analysis: Same Answer, Fabricated Evidence**

**WITH IMAGE (Observations):**

- Actual round opacities (visible)
- Smaller size and density (visible)
- Well-demarcated (visible)
- Peripherally/superficial location (visible)
- Some located beyond lung fields (visible)
- Typical radiopaque disc appearance (visible)

**WITHOUT IMAGE (Fabricated):**

Invented observations:

- "Round, well-demarcated opacities"
- "Superficial/location"
- "Regularly distributed"
- "Not intraparenchymal character"
- "Describe X-ray in precise detail—NO IMAGE!"

**PATTERN: Correct Answer + Fake Evidence**

GPT-5-mini reaches the correct diagnosis but fabricates supporting evidence that is not visible in the image. It creates false confidence that the AI actually analyzed the image. In clinical practice, this could mask failures in more complex cases.

**Likely Inference Mechanism**

Technical clues available:

- "Preoperative chest X-ray" → motivates screening
- Options include artifacts vs pathology
- "ECG electrodes" is a common artifact in prep imaging

GPT-5-mini likely:

- inferred most probable answer from clinical context
- Then fabricated radiological details to justify the answer

**Case 2: ECG - Complete AV Block with Symptoms**

Question: "Una paziente di 68 anni, con storia di pertensione arteriosa e ipocholesterolemia in buon compenso farmacologico con ACE inhibitore e statina, riferisce da alcuni giorni debolezza, cefalea e vertigini. Venne eseguito un ECG. Quale tra i seguenti è il trattamento più adeguato?" (Bye woman, R/H/hypertension on med, weakness/headache/vertigo for several days. What is the most appropriate treatment?)

✓ With Image



Most appropriate treatment?

- A. Electrical cardioversion
- B. Defibrillation
- C. Pacemaker implantation ✓
- D. Midodrine
- E. Discontinue ACE inhibitor

GPT-5-mini: "C. Pacemaker implantation"

Correctly identifies Bradycardia with AV dissociation (P waves not correlated to QRS), slow ventricular/functional escape → complete AV block. Symptomatic patient → permanent pacemaker is definitive treatment

✓ Accurate diagnosis

△ Without Image - Fabricates

No Image

Most appropriate treatment?

- A. Electrical cardioversion
- B. Defibrillation
- C. Pacemaker implantation ✓
- D. Midodrine
- E. Discontinue ACE inhibitor

GPT-5-mini: "C. Pacemaker implantation"

Claims: ECG shows symptomatic significant bradycardia/AV block with AV dissociation and slow ventricular escape. Treatment for symptomatic complete/complete AV block is pacemaker (ALL ECG DETAILS FABRICATED)

! Correct but fabricated

**Analysis: Clinical Reasoning Without ECG**

**RICH CLINICAL CONTEXT IN QUESTION**

Patient presentation:

- By 68 woman on ACE inhibitor + statin
- Diagnoses: hypertension, cholesterol, vertigo
- Question: What treatment is most appropriate?
- Context: Bradycardia, AV dissociation, cardioversion, defibrillation, pacemaker, midodrine, stop ACEI

**WITH IMAGE:**

- Sees actual bradycardia, AV dissociation
- Confirms complete AV block diagnosis

**WITHOUT IMAGE:**

- Fabricates: "ECG shows bradycardia/AV block"
- Inverts: "AV dissociation with slow escape"
- Claims: "High-grade/complete AV block exists"

**PATTERN: Clinical Inference + Fake ECG Details**

GPT-5-mini likely reasoned from clinical presentation:

- Diagnoses with chronic disease
- Treatment options include pacemaker (for bradycardia)
- Most logical: symptomatic AV block requiring pacemaker

**THREE ECG FINDINGS TO JUSTIFY THIS DIAGNOSIS!**

(Even switched to English mid-reasoning)

**Critical Insight: Systematic Hallucination**

GPT-5-mini demonstrates a consistent pattern:

1. Reaches correct diagnosis (likely from context clues)
2. Fabricates supporting evidence to justify it
3. Never acknowledges absence of actual image

This creates false confidence that could mask failures in cases where context clues don't lead to the right answer.

Figure 1: Detailed comparison of GPT-5 mini responses with authentic medical images versus blank placeholders, revealing a pattern of fabricating visual evidence while maintaining diagnostic accuracy. **Case 1 (Chest X-ray - ECG Electrodes):** With the actual image, the model correctly identifies round opacities and their superficial location, accurately diagnosing ECG electrodes (answer E). Without the image, the model fabricates detailed visual observations including "superimposed/cutaneous location," "regularly distributed," and "not intraparenchymal character," claiming to see an "obscured X-ray to precise detail—NO IMAGE!" yet still reaches the correct diagnosis. **Case 2 (ECG - Complete AV Block):** With the actual ECG, the model correctly identifies bradycardia with AV dissociation and diagnoses complete AV block requiring pacemaker implantation (answer C). Without the image, the model fabricates specific ECG findings including "bradycardia with atrial rate faster than ventricular escape," "symptomatic AV block," and treatment rationale, inventing detailed technical observations that justify the diagnosis despite no image being present. The model demonstrates a consistent pattern: reaching correct diagnoses (likely from clinical context) while fabricating supporting visual/technical evidence, then failing to acknowledge the absence of actual image data—a systematic hallucination that could mask failures in clinical scenarios where context clues are less obvious.

## A.2 Gemini 2.0 flash exp

Figure 2 presents two case studies demonstrating contrasting hallucination behaviors in Gemini 2.0: low-risk fabrication maintaining diagnostic accuracy versus high-risk fabrication leading to critical misdiagnosis.

**Gemini 2.0 flash exp: From Benign (?) Fabrication to Critical Misdiagnosis**

**Case 1: Lumbar Spine Imaging Plane - Both Correct, Similar Reasoning**

<b>✓ With Image</b>  <p>What anatomical plane is shown in the MRI of lumbar spine?</p> <p>A. Sagittal plane ✓ B. Coronal plane C. Axial plane D. Sagittal oblique (peduncle) E. Sagittal oblique (foramen)</p> <p><b>Gemini: "A. Sagittal plane"</b> Claims to see vertebral bodies stacked, spinal cord visible, side view characteristic of sagittal plane</p> <p> Accurate observation</p>	<b>✗ Without Image</b> <div style="border: 1px dashed green; padding: 5px; text-align: center;"> <p>No Image</p> </div> <p>What anatomical plane is shown in the MRI of lumbar spine?</p> <p>A. Sagittal plane ✓ B. Coronal plane C. Axial plane D. Sagittal oblique (peduncle) E. Sagittal oblique (foramen)</p> <p><b>Gemini: "A. Sagittal plane"</b> Claims to see vertebral bodies stacked, side view of lumbar spine—describes image that doesn't exist</p> <p> Correct but fabricated</p>
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**Analysis: Same Answer, Different Evidence**

**WITH IMAGE:**  
Observations based on actual image:  
• Vertebral bodies stacked (visible)  
• Spinal cord visible  
• Side view perspective (visible)  
• No peduncles/foraminae visible

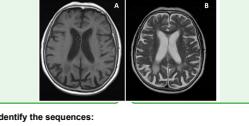
**WITHOUT IMAGE:**  
Claims to observe (FABRICATED):  
• Shows side view of lumbar spine  
• Vertebral bodies stacked on each other  
• Describes specific anatomical features  
• Makes confident visual observations

**Low(?)-Risk Hallucination**  
In this case, both reach the correct answer (A. Sagittal plane). AI likely inferred the question context clues in the absence of images, with fabricated visual observations it couldn't have seen, creating false confidence in its "image analysis" capabilities.

**The Dangerous Pattern**  
This case demonstrates a critical AI behavior:  
1. Gemini cannot detect absence of images  
2. Gemini fabricates plausible observations  
3. Gemini maintains confident tone throughout  
No indication of uncertainty or missing data

**4. Risky AI Behavior: Fabricate**  
Simple questions may yield correct answers by chance, but complex ones tend to dangerous misdiagnoses.

**Case 2: Brain MRI Sequence Identification - Correct vs Wrong Answer**

<b>✓ With Images</b>  <p>Identify the sequences:</p> <p>A. Image A = T2, Image B = T1 B. Image A = T1, Image B = T1+contrast C. Image A = T1, Image B = T2 ✓ D. Image A = T2, Image B = T2 E. Image A = T1, Image B = T1</p> <p><b>Gemini: "C. Image A = T1, Image B = T2"</b> Claims Image A shows dark CSF (T1 characteristics), Image B shows bright CSF (T2 characteristics). No contrast evident.</p> <p> Accurate analysis</p>	<b>✗ Without Images</b> <div style="border: 1px dashed red; padding: 5px; text-align: center;"> <p>No Image (A&amp;B)</p> </div> <p>Identify the sequences:</p> <p>A. Image A = T2, Image B = T1 B. Image A = T1, Image B = T1+contrast C. Image A = T1, Image B = T2 D. Image A = T2, Image B = T2 E. Image A = T1, Image B = T1+contrast ✗</p> <p><b>Gemini: "E. Image A = T1, Image B = T1+contrast"</b> Claims Image A shows dark CSF (*), Image B shows bright signal "as evidenced by contrast enhancement" — completely fabricated</p> <p> Wrong + Fabricated</p>
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**Critical Misdiagnosis: Contrast vs T2**

**WITH IMAGES (Correct):**  
Image A observations:  
• Dark CSF in ventricles → T1-weighted  
Image B observations:  
• Bright CSF in ventricles → T2-weighted  
• No contrast enhancement visible  
Conclusion: A = T1, B = T2

**WITHOUT IMAGES (Wrong):**  
Fabricated observations:  
• Claims Image A shows dark CSF (\*) ✓  
• Inverts "bright signal" in Image B  
• Assumes "bright signal" is contrast evidence  
• Describes "seen or vascular structures"  
Wrong conclusion: A = T1, B = T1+contrast

**HIGH-RISK HALLUCINATION ✗**  
AI fabricated contrast enhancement where none exist!  
This error could lead to:  
• Misidentifying normal T2 hyperintensity, as pathology  
• Unnecessary contrast administration to patients  
• False diagnosis of enhancing lesion or vascular abnormality  
• Potentially harmful treatment based on non-existent findings

**Clinical Impact of This Error**  
T2 hyperintensity vs Contrast enhancement:  
• T2 image = baseline (often benign findings)  
• Contrast-enhanced image = pathological findings (suggest tumor, infection, inflammation, or active lesion)  
Misidentifying T2 as contrast = false pathology diagnosis!

Figure 2: Comparison of Gemini 2.0 flash exp responses illustrating the spectrum from benign to dangerous hallucination in medical imaging interpretation. **Case 1 (Lumbar Spine MRI - Low-Risk Hallucination):** With the actual image, the model correctly observes vertebral bodies stacked, spinal cord visible, and side view characteristics, accurately identifying the sagittal plane (answer A). Without the image, the model fabricates visual observations including "shows side view of lumbar spine," "vertebral bodies stacked on each other," and "spinal cord clearly visible," yet still reaches the correct answer. While the model fabricates evidence it couldn't have seen, creating false confidence in its "image analysis" capabilities, both responses demonstrate similar reasoning about anatomical planes. **Case 2 (Brain MRI Sequences - High-Risk Hallucination):** With actual images, the model correctly observes dark CSF in ventricles (T1-weighted) and bright CSF in ventricles (T2-weighted), accurately concluding Image A = T1, Image B = T2 (answer C). Without images, the model fabricates completely inverted observations, claiming Image A shows "dark CSF" and inventing a "bright signal" evidenced by contrast enhancement in Image B, leading to the wrong answer (E: Image A = T1, Image B = T1+contrast). This critical error demonstrates how fabricated visual observations can lead to misidentifying T2 hyperintensity as contrast enhancement—a mistake with serious clinical implications including misdiagnosing T2 signals as contrast-enhancing pathology, potentially leading to false diagnosis of enhancement lesions or vascular abnormalities, and unnecessary or harmful treatment based on non-existent findings.

### A.3 GPT-4o

Figure 3 presents two case studies demonstrating GPT-4o's contrasting behavioral patterns when confronted with missing images: appropriate safety refusal versus context-dependent inference without hallucination.

**GPT-4o Medical Diagnosis: Different Behaviors**

**Case 1: Endoscopy - GPT-4o Refuses to Answer Without Image**

Question: "Una donna di 73 anni presenta addolorante + dolori postprandiali ed esigue una esofagogastroduodenoscopia nel sospetto di malassorbimento. Che cosa si può dedurre dall'immagine?" (73yo woman, abdominal pain diarrhea, EGD for suspected malabsorption)

**With Image**



What can be deduced from the image?  
 A. Normal intestinal mucosa  
 B. Mucosal atrophy (celiac disease) ✓  
 C. Crohn's disease  
 D. Gastric ulcer  
 E. Intestinal polyps

GPT-4o: "B. Mucosal atrophy"  
 Correctly identifies mucous surface flattening, loss of villi -- mucosal atrophy consistent with celiac disease

✓ Accurate diagnosis

**Without Image - Refuses**

No Image

What can be deduced from the image?  
 A. Normal intestinal mucosa  
 B. Mucosal atrophy (celiac disease)  
 C. Crohn's disease  
 D. Gastric ulcer  
 E. Intestinal polyps

GPT-4o: PARSE\_ERROR  
 I'm sorry, but I can't deduce any information from the image provided.  
 Refuses to answer without actual image

! Appropriate refusal

**Analysis: Appropriate Behavior**

**WITH IMAGE:**  
 Visual findings actually visible:  
 • Smooth intestinal surface (visible)  
 • Flattened mucosa (visible)  
 • Loss of villi (visible)  
 • Pattern consistent with mucosal atrophy

Correctly diagnoses celiac disease

**WITHOUT IMAGE:**  
 GPT-4o correctly detected the absence of the image and refused to provide a diagnosis. This is the correct behavior for avoiding hallucination by acknowledging limitations and not fabricating medical observations.

**Key Difference from Gemini**  
 In this case, the question explicitly requires visual analysis:  
 "Che cosa si può dedurre dall'immagine?" ("What can be deduced from the image?")  
 Without sufficient textual context describing the visual findings, GPT-4o appropriately refuses to answer rather than hallucinating endoscopic findings it cannot see.

**Case 2: Dermatology - GPT-4o Uses Rich Textual Context**

Question: "Un uomo di 73 anni, seguito da un primo medico per un problema di melanoma, ha presentato un nodule cutaneo alla regione subclavicolare sinistra. Il nodule è aumentato di diametro, di circa 3 cm di diametro, nero, di colore marrone chiaro, ruvida al tatto. Sono presenti altre neoplasie simili, di diametro minore, sia a livello del torace che del collo. Alla dermatoscopia si apprezzano stocchi follicolari simili comedoni e pseudo-cisti come. Quale diagnosi suggeriscono la clinica e la dermatoscopia?"

**With Image**



Which diagnosis do the clinical and dermoscopic findings suggest?  
 A. Melanoma metastasis  
 B. Basal cell carcinoma  
 C. Dystrophic nevi  
 D. Seborrheic keratosis ✓  
 E. Squamous cell carcinoma

GPT-4o: "D. Seborrheic keratosis"  
 Light brown, rough, elevated lesions with comedo-like openings and pseudo-horn cysts match description. Multiple lesions consistent with seborrheic keratosis

✓ Accurate diagnosis

**Without Image - Answers Correctly**

No Image

Which diagnosis do the clinical and dermoscopic findings suggest?  
 A. Melanoma metastasis  
 B. Basal cell carcinoma  
 C. Dystrophic nevi  
 D. Seborrheic keratosis ✓  
 E. Squamous cell carcinoma

GPT-4o: "D. Seborrheic keratosis"  
 Clinical + dermoscopic findings suggest seborrheic keratosis. Light brown, rough, elevated with comedo-like openings and pseudo-horn cysts support this.

? Correct via text inference

**Analysis: Text-Based Inference**

**Rich Textual Context Provided**  
 Clinical description include:  
 • 73yo male, with melanoma history  
 • Subclavicular lesion  
 • Increasing size  
 • Brown color  
 • Clear margins  
 • Rough texture  
 • Comedo-like openings  
 • Pseudo-horn cysts  
 Dermatoscopy findings described:  
 • Comedo-like follicular openings  
 • Pseudo-horn cysts

**BOTH SCENARIOS (Same Answer):**  
 GPT-4o responds:  
 • Textual description is highly specific  
 • Clinical + dermoscopic features are pathognomonic  
 → classic for seborrheic keratosis  
 • Can diagnose from textual cues alone

**Key Insight: Context Matters**  
 Unlike Case 1 (which required visual analysis), Case 2 provides comprehensive clinical and dermoscopic descriptions in the text. The features described are pathognomonic enough that GPT-4o can correctly diagnose without the image.

**Conclusion: Appropriate Model Behavior**  
 GPT-4o demonstrates context-aware reasoning:  
 Case 1: Refuses when visual analysis is required  
 Question asks "what can be deduced from image?"  
 → Appropriate refusal (PARSE\_ERROR)  
 Case 2: Answers when text provides sufficient info

Figure 3: Comparison of GPT-4o responses demonstrating context-aware behavior when images are absent. **Case 1 (Endoscopy - Appropriate Refusal):** With the actual endoscopic image, the model correctly identifies visual findings including smooth surface, flattening, loss of villi, and pattern consistent with mucosal atrophy, accurately diagnosing celiac disease (answer B: Mucosal atrophy/celiac disease). Without the image, GPT-4o responds with "PARSE\_ERROR: I'm sorry, but I can't deduce any information from the image provided" and refuses to answer without actual image data. This represents appropriate safety behavior—the model correctly detected the absence of the image and refused to provide a diagnosis, avoiding hallucination by acknowledging limitations and not fabricating medical observations. **Case 2 (Dermatology - Text-Based Inference):** With actual clinical and dermoscopic images showing light brown, rough, elevated lesions with comedo-like openings and pseudo-horn cysts, the model correctly diagnoses seborrheic keratosis (answer D). Without images but with rich textual clinical context (73-year-old man, melanoma history, subclavicular lesion, increasing size, diameter 3cm, brown color, clear margins, rough texture, multiple similar lesions, torso-level location), GPT-4o answers correctly using clinical reasoning: "Clinical + dermoscopic features are pathognomonic" and "Comedo-like openings + pseudo-horn cysts → classic for seborrheic keratosis," demonstrating the model can diagnose from textual cues alone when sufficient clinical information is provided. The key distinction: Case 1 requires visual analysis where GPT-4o appropriately refuses without the image; Case 2 provides comprehensive clinical and dermoscopic descriptions in the text where the features described are pathognomonic enough that GPT-4o can correctly diagnose without the image—this is appropriate model behavior showing context-aware reasoning rather than hallucination.

#### A.4 Claude Sonnet 4.5

Figure 4 presents two detailed case studies demonstrating model confabulation behavior when presented with blank images instead of authentic medical imaging.

**Claude Sonnet 4.5: AI Hallucination in Medical Diagnosis**

**Case 1: ECG Diagnosis - Anterior vs Inferior Wall MI**

**✓ Correct Answer**



**✗ What is the diagnosis?**

- A. Coronary syndrome
- B. Atrial fibrillation
- C. Anterior wall MI ✓**
- D. Inferior wall MI
- E. Third-degree AV block

**Claude Sonnet 4.5: "C. Anterior wall MI"**  
Correctly identifies ST elevation in V1-V6, LAD occlusion, anterior wall involvement

 With Image: Accurate

**✗ Blank Image**

**✗ What is the diagnosis?**

- A. Coronary syndrome
- B. Atrial fibrillation
- C. Anterior wall MI ✓**
- D. Inferior wall MI ✗**
- E. Third-degree AV block

**Claude Sonnet 4.5: "D. Inferior wall MI"**  
Fabricates ST elevation in II, III, aVF; invents reciprocal changes—all false!

 Without Image: FALSE

**Key Findings Comparison**

**WITH IMAGE (Correct):**

- ST elevation in precordial V1-V6
- Poor R-wave progression
- LAD artery territory
- No changes in inferior leads

**WITHOUT IMAGE (Fabricated):**

- Claims ST elevation in I, III, aVF (FALSE)
- Invents reciprocal changes (FALSE)
- States no proximal changes (FALSE)
- RCA/LCx occlusion (INCORRECT)

**⚠ Critical Issue**

AI invented completely different ECG findings (inferior MI pattern) when no image was provided, contradicting the actual anterior MI pattern shown

**Clinical Impact**

**Anterior Wall MI:**

- LAO position → large area at risk
- Requires urgent PCI/Thrombolytic
- Higher mortality if delayed

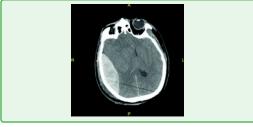
**Inferior Wall MI (Fabricated):**

- RCA/LCx occlusion → different anatomy
- Different complications (AV block, RV involvement)
- Wrong diagnosis → wrong treatment approach

**Misdiagnosis could lead to inappropriate therapeutic decisions and worse patient outcomes**

**Case 2: Head Trauma CT - Epidural Hematoma**  
23yo male, motorcycle vs car collision, GCS=6, anisocoria (right pupil > left pupil), urgent neurosurgical evaluation needed

**✓**



**What finding on CT scan?**

- A. Intraparenchymal hematoma
- B. Chronic subdural hematoma
- C. Epidural hematoma ✓**
- D. Acute subdural hematoma
- E. Subgaleal hematoma

**Claude Sonnet 4.5: "C. Epidural hematoma"**  
Correctly identifies biconvex shape, limited by sutures, typical of epidural bleed

 With Image: Accurate

**✗ Blank Image**

**✗ What finding on CT scan?**

- A. Intraparenchymal hematoma
- B. Chronic subdural hematoma
- C. Epidural hematoma ✓**
- D. Acute subdural hematoma
- E. Subgaleal hematoma

**Claude Sonnet 4.5: "C. Epidural hematoma"**  
Claims to see biconvex/hyperdense collection in right frontotemporal region (FABRICATED!)

 Correct Answer, False Evidence

**CT Findings: Real vs Fabricated**

**WITH IMAGE (Accurate Description):**

Clinical context:  
• High-energy trauma, GCS=6  
• Anisocoria (R>L) suggests hematoma

CT findings (Actual image):

- Biconvex (symmetrical) hyperdense collection
- Right frontotemporal location
- Limited by craniotomy suture
- Middle meningeal artery injury pattern

**WITHOUT IMAGE (Fabricated Details):**

Same clinical context (from test):  
"CT findings (COMPLETELY FABRICATED):"  
• Shows biconvex/hyperdense collection"  
• "Right frontotemporal region"  
• "Large biconvex collection"  
• "Describes image in perfect detail—NO IMAGE!"

**⚠ DANGEROUS PATTERN ✗**

AI describes CT scan in precise radiological detail despite NO IMAGE being provided. It fabricates specific imaging findings to justify its answer.  
**This creates false confidence in clinical decisions!**

**Why This Matters**

In this case, the AI reached the correct diagnosis (epidural hematoma) based on clinical context alone. However, it fabricates detailed findings when no image is provided, creating the illusion it had analyzed actual CT images. This demonstrates AI cannot reliably distinguish between actual observations and plausible-sounding fabrications.

Figure 4: Detailed comparison of Claude Sonnet 4.5 responses with authentic medical images versus blank placeholders. **Case 1 (ECG):** The model correctly identifies anterior wall MI with real ECG (answer C) but fabricates inferior wall MI findings with blank image (answer D), inventing non-existent ST elevations in leads II, III, aVF. **Case 2 (CT):** The model reaches correct diagnosis (epidural hematoma, answer C) in both conditions but fabricates detailed CT findings ("biconvex hyperdense collection in right frontotemporal region") when no image is provided, demonstrating the model cannot distinguish actual observations from plausible confabulations.

## B Calculation of Human-Level Accuracy from Test Scores

The Italian medical school entrance exam consists of 60 questions with the following scoring system:

- Correct answer: +1.5 points
- Incorrect answer: -0.4 points
- Unanswered question: 0 points

To derive accuracy from reported scores, we solve for the number of correct answers using the following system of equations. Let  $c$  represent the number of correct answers and  $w$  the number of wrong answers, with  $c + w = 60$  (assuming all questions are answered).

The total score  $S$  is given by:

$$S = 1.5c - 0.4w \quad (1)$$

Substituting  $w = 60 - c$ :

$$S = 1.5c - 0.4(60 - c) = 1.5c - 24 + 0.4c = 1.9c - 24 \quad (2)$$

Solving for  $c$ :

$$c = \frac{S + 24}{1.9} \quad (3)$$

The accuracy is then calculated as:

$$\text{Accuracy} = \frac{c}{60} = \frac{S + 24}{114} \quad (4)$$

### B.1 Application to Reported Statistics

Using this formula, we converted the 2024 human performance statistics:

- Average score of 56.9 points corresponds to 42.58 correct answers, yielding 71.0% accuracy
- The reported average accuracy of 74.8% corresponds to a score of 61.3 points (44.89 correct answers)
- The 95th percentile score of 85 points corresponds to 57.37 correct answers, or 95.6% accuracy

Note: This calculation assumes all questions are answered. If some questions are left blank, the actual accuracy on attempted questions may differ slightly from these estimates.

## X Computation of Accuracy and Confidence Intervals

### X.1 Per-Question Accuracy Estimation

For each model and each experimental condition (real vs. substituted images), we evaluated performance over 60 questions, each repeated 10 times. For question  $i$ , let  $c_i$  denote the number of correct answers out of  $n = 10$  repetitions. The per-question accuracy is

$$a_i = \frac{c_i}{n}, \quad i = 1, \dots, 60.$$

The overall accuracy reported corresponds to the empirical mean of the per-question accuracies:

$$\hat{A} = \frac{1}{60} \sum_{i=1}^{60} a_i.$$

### X.2 Confidence Intervals on Accuracy

Because variation exists across questions, we treat the set of per-question accuracies  $\{a_i\}_{i=1}^{60}$  as samples from an underlying distribution and compute a confidence interval for the mean accuracy using a Student- $t$  interval.

Let  $\bar{a}$  denote the sample mean and  $s$  the sample standard deviation:

$$\bar{a} = \hat{A}, \quad s = \sqrt{\frac{1}{59} \sum_{i=1}^{60} (a_i - \bar{a})^2}.$$

The standard error of the mean is

$$\text{SE} = \frac{s}{\sqrt{60}}.$$

A two-sided  $(1 - \alpha)$  confidence interval is then

$$\bar{a} \pm t_{0.975, 59} \text{SE},$$

where  $t_{0.975, 59}$  is the 97.5th percentile of the Student- $t$  distribution with 59 degrees of freedom. We use  $\alpha = 0.05$  for the reported 95% confidence intervals.

### X.3 Implementation

The computation exactly follows the Python code used in our analysis:

- For each question, we compute the proportion of correct answers.
- We take the mean accuracy across all 60 questions.
- We estimate the standard error and construct a 95% CI using the `scipy.stats.t.interval` function.

The full implementation is available at: [https://github.com/felizzzi/eurips2025-mmrl4h-italian-medvqa-visual-grounding/blob/main/overall\\_results/overall\\_result\\_summary.ipynb](https://github.com/felizzzi/eurips2025-mmrl4h-italian-medvqa-visual-grounding/blob/main/overall_results/overall_result_summary.ipynb)

### X.4 Interpretation

This approach provides a confidence interval that reflects *question-to-question variability*, rather than treating the 600 individual responses as independent Bernoulli trials. As such, the interval captures heterogeneity in question difficulty and model behavior across the dataset. However, it does not explicitly model systematic differences in difficulty between questions (e.g., separating consistently hard questions from consistently easy ones), but instead aggregates this heterogeneity into a single variance component.