RESEARCH PAPER

Beyond Aggregate Accuracy: A Multiaxis Evaluation Framework for Clinical Vision-Language Systems

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Abstract

Clinical deployment of multimodal foundation models requires evidence that extends beyond summary accuracy metrics. When deep vision-language architectures are evaluated solely through scalar discrimination indices such as top-1 accuracy or area under the receiver operating characteristic curve, critical failure modes remain obscured. Models that appear statistically equivalent under aggregate evaluation often exhibit dramatic disparities in calibration, semantic consistency under clinical paraphrasing, subgroup vulnerability, and downstream decision utility. This paper establishes a formal multiaxis evaluation framework specifically formulated for clinical vision-language systems. We formalize evaluation across four orthogonal dimensions: discriminative capability, uncertainty calibration and reliability, linguistic robustness under semantic-preserving perturbations, and workflow risk-coverage trade-offs. We prove that single-index summaries introduce irreversible information loss that can mask severe safety vulnerabilities in medical triage. Through an illustrative evaluation protocol spanning 1,200 chest radiograph diagnostic queries with paired semantic variations, we demonstrate how multidimensional auditing uncovers latent instability. We formulate rigorous diagnostic estimands, define operational validity checks, and synthesize evidence across contemporary evaluation benchmarks. Our framework provides clinical AI developers, hospital procurement committees, and regulatory bodies with an axiomatic methodology to evaluate whether vision-language models satisfy the safety and reliability thresholds required for high-stakes healthcare deployment.

1. Introduction

The integration of artificial intelligence into clinical radiology, emergency medicine, and critical care diagnostics marks an architectural inflection point in computational healthcare informatics [1]. For over a decade, clinical machine learning was defined by task-specific, supervised convolutional neural networks engineered to execute narrow visual classification or semantic segmentation on rigidly standardized pixel matrices [2]. While these specialized discriminative models achieved impressive diagnostic benchmarks on curated challenge datasets, their practical translational utility was consistently impeded by their inability to ingest clinical context, interpret clinical histories, or interact with medical specialists through flexible natural language interfaces [3]. The emergence of large-scale multimodal vision-language foundation models has fundamentally reshaped this translational paradigm [4]. Jointly training expressive vision transformers and autoregressive language backbones over massive corpora of medical imaging paired with radiological reports, clinical narratives, and electronic health record documentation endows vision-language architectures with unprecedented capabilities in zero-shot diagnostic inference, anatomical reasoning, and interactive clinical question answering [5].

In routine clinical workflows, diagnostic decision-making is inherently multimodal, contextual, and conversational [6]. Radiologists, attending physicians, and triage nurses do not evaluate diagnostic imaging in an informational vacuum; rather, they dynamically synthesize visual anatomical structures with clinical indications, bedside vital signs, laboratory markers, and prior longitudinal imaging studies [7]. Vision-language models hold the potential to serve as tireless, expert-level diagnostic assistants capable of performing preliminary triage, drafting comprehensive radiological findings, flagging subtle life-threatening emergencies, and communicating diagnostic rationale to healthcare providers in real time [8]. In resource-constrained global health settings, where severe shortages of subspecialty radiologists lead to substantial diagnostic delays and preventable patient morbidity, the deployment of reliable multimodal AI systems could substantially democratize access to timely and accurate radiological interpretation [9].

However, the clinical translation of multimodal vision-language systems is currently confronted by a profound evaluation crisis [10]. Prevailing validation protocols in the machine learning literature remain overwhelmingly reliant on aggregate, scalar discrimination metrics [11]. The vast majority of published studies evaluate medical foundation models by computing the area under the receiver operating characteristic curve (AUC-ROC), the area under the precision-recall curve (AUPRC), macro-averaged F1-scores, or top-1 classification accuracy across stationary, retrospective test collections [12]. While these summary statistics provide a useful global index of statistical ranking ability across a cohort, they suffer from severe mathematical and operational limitations [13]. Compressing thousands of complex, heterogeneous patient interactions into a single scalar value inevitably leads aggregate metrics to obscure catastrophic localized failure modes, acute subgroup vulnerabilities, and severe operational instabilities that can directly cause clinical harm [14].

In clinical healthcare environments, an algorithmic system that achieves a nominally outstanding aggregate AUC of 0.90 may nevertheless exhibit alarming unreliability under routine operational variations [15]. Unlike academic benchmark environments where evaluation queries are standardized and uniform, hospital workflows are characterized by extensive linguistic, demographic, and operational heterogeneity [16]. Clinicians across different training backgrounds, subspecialties, hospital networks, and native languages express identical diagnostic inquiries using widely disparate syntax, vocabulary, prompt lengths, and framing conventions [17]. An emergency physician might evaluate a portable chest radiograph by asking, "Is there evidence of a right-sided tension pneumothorax?" while a pulmonary fellow examining the exact same patient might enter, "Evaluate the right hemithorax for pleural separation and pneumothorax," and a triage nurse might query, "Check whether pneumothorax can be ruled out." In an ethically acceptable and safe clinical decision support system, the algorithmic determination and its associated posterior uncertainty must demonstrate robust invariance to such semantically equivalent syntactic variations [18].

Recent empirical investigations, however, have revealed that modern medical vision-language foundation models exhibit astonishing fragility when confronted with adversarial prompts and subtle perturbations. In their comprehensive security evaluation, Sadanandan and Behzadan introduce VSF-Med, establishing an eight-axis vulnerability scoring framework evaluated by dual independent judge models across 30,000 adversarial variants from 5,000 radiology images, and demonstrate that leading vision-language architectures suffer substantial vulnerability shifts—including mean z-score increases of 0.90œ for persistence of attack effects and 0.74œ for prompt injection—providing a concrete demonstration of why clinical model evaluation must assess multidimensional robustness alongside accuracy [19]. When an artificial intelligence architecture alters its categorical clinical verdict—transitioning from identifying an acute, life-threatening pleural pathology to declaring an entirely normal lung—purely as a consequence of minor, semantically neutral prompt paraphrasing, the aggregate accuracy metric ceases to serve as an indicator of diagnostic competence. Instead, it masks an underlying stochastic vulnerability that renders the model unsafe for autonomous or semi-autonomous clinical deployment [20]. If an algorithm's diagnostic output fluctuates based on the arbitrary syntactic phrasing of the attending clinician on duty, patient safety is severely compromised, and institutional trust in computational tools collapses [21].

Furthermore, scalar evaluation fails to capture the multidimensional nature of clinical risk [1]. A truly reliable clinical AI system must excel simultaneously along several distinct operational axes:

- **Axis I: Discriminative Precision and Statistical Calibration**: The system must maintain high sensitivity and specificity across diverse disease severities while ensuring that its predicted posterior confidence accurately reflects the true mathematical probability of pathology, avoiding dangerous overconfidence on borderline presentations.
- **Axis II: Semantic Robustness and Workflow Deferral Utility**: The system must preserve strict decision invariance across clinically equivalent linguistic variations while effectively identifying its own epistemic boundaries to defer highly ambiguous cases to human specialists under bounded clinical alert budgets.

The necessity of multiaxis auditing becomes even more pressing when considering the cognitive workflow of human clinicians interacting with automated systems [2]. Clinicians are not passive recipients of algorithmic outputs; they actively interpret machine recommendations in the context of their own diagnostic expectations, clinical heuristics, and institutional protocols [3]. When an AI system presents miscalibrated confidence scores—such as asserting high certainty on erroneous conclusions—clinicians are prone to automation bias, inappropriately overriding their clinical judgment and accepting incorrect recommendations [4]. Conversely, if a system displays erratic fluctuations in response to minor linguistic rephrasings, clinicians rapidly lose confidence in the technology, leading to algorithmic aversion and the complete abandonment of potentially beneficial decision support tools [5]. A multiaxis evaluation framework that explicitly measures both calibration fidelity and linguistic stability provides the foundational transparency necessary to foster appropriate, calibrated human-machine trust.

In addition to calibration and robustness, the operational success of clinical vision-language systems depends fundamentally on their capacity to integrate seamlessly into hospital referral and triage workflows [6]. In emergency departments and intensive care units, clinical resources are severely constrained by finite personnel, diagnostic imaging slots, and specialist consultation capacity [7]. An algorithm that issues uncurated alerts for every suspicious finding will inevitably induce severe alert fatigue, leading clinicians to ignore critical warnings [8]. A clinical AI system must therefore possess a well-defined rejection option, enabling it to autonomously process routine, low-risk cases where it possesses high epistemic certainty while selectively deferring complex, ambiguous, or borderline examinations to expert subspecialists [9]. Evaluating models across a continuous risk-coverage frontier allows hospital administrators to establish precise operating thresholds that match institutional triage capacities and specialized staffing levels [10].

To resolve these fundamental challenges, this article establishes a formal, axiomatic multiaxis evaluation framework specifically formulated for clinical vision-language systems. Through rigorous mathematical definitions, operational evaluation protocols, and standardized diagnostic estimands, we demonstrate how multidimensional auditing uncovers latent model vulnerabilities that remain completely invisible under conventional aggregate benchmarks. In the subsequent sections, we establish the mathematical foundations of multiaxis evaluation, detail the operational protocols for stress-testing clinical foundation models, present empirical evidence from a multi-center radiographic cohort, and discuss institutional

governance pathways for clinical translation.

Historically, the evaluation of clinical diagnostic software has been shaped by the legacy of biometric screening and epidemiological testing methodologies formulated in the mid-twentieth century [1]. When diagnostic assays were biochemical, physical, or based on isolated biometric parameters, reporting sensitivity, specificity, and receiver operating characteristic profiles provided an exhaustive description of diagnostic efficacy [2]. In that traditional paradigm, the input to the diagnostic test was invariant: a blood serum sample or an electrocardiographic lead voltage does not rephrase its physiological state based on who draws the vial or operates the machine [3]. The advent of conversational and instruction-tuned vision-language architectures has shattered this foundational invariance assumption [4]. Because natural language serves as the conditioning interface, the diagnostic system is subjected to an infinite variety of syntactic, stylistic, and semantic prompt formulations [5]. Evaluating such interactive, generative systems using static biometric metrics creates a dangerous mismatch between the multidimensionality of the model's operational manifold and the scalar simplicity of the evaluation score [6].

The consequences of this evaluation mismatch are particularly acute in acute clinical care, where diagnostic decisions are executed under extreme cognitive pressure and temporal constraints [7]. In emergency departments, intensive care units, and acute trauma resuscitation bays, clinical communication is naturally compressed, variable, and hurried [8]. Healthcare providers rely heavily on idiosyncratic shorthand, situational phrasing, and verbal queries that diverge sharply from the pristine, grammatically uniform sentences found in academic training benchmarks [9]. If an artificial intelligence system requires brittle syntactic compliance to maintain diagnostic fidelity, its clinical utility is fundamentally compromised [10]. Under emergency conditions, an attending clinician cannot be burdened with memorizing opaque prompt engineering rules or attempting multiple query reformulations to verify whether an algorithm's initial negative reading was a genuine reflection of patient anatomy or merely an artifact of an unfavorable sentence structure [11].

Moreover, modern medical foundation models possess billions of parameters and demonstrate complex emergent behaviors that cannot be understood through black-box accuracy testing [12]. Deep neural representations are notoriously vulnerable to texture bias, spurious background correlations, and language-prior shortcuts [13]. In medical imaging, models often learn to exploit non-pathological visual cues—such as radiopaque hospital orientation markers, patient body habitus, portable scanner artifacts, or support apparatus (e.g., endotracheal tubes, chest drains, electrocardiogram wires)—to infer disease presence without detecting true pathological tissue alterations [14]. When language conditioning is introduced, these visual shortcuts interact with linguistic priors in unpredictable ways [15]. A query containing authoritative clinical terminology can artificially inflate model confidence, leading the architecture to hallucinate radiographic findings that do not exist, whereas a tentative or inquisitive inquiry may suppress legitimate pathological detections [16]. Decoupling evaluation into distinct, orthogonal axes provides the analytical resolution needed to detect these cross-modal confounding interactions before systems are integrated into patient care [17].

The urgency of establishing rigorous multiaxis evaluation standards is further underscored by the growing convergence between multimodal foundation models and autonomous agentic workflows in clinical informatics [1]. In forward-looking hospital architectures, vision-language models are no longer deployed merely as isolated, passive diagnostic predictors; they are increasingly granted agency to query longitudinal patient databases, synthesize multi-organ clinical histories, draft formal diagnostic reports for radiological over-reading, and communicate directly with bedside nursing telemetry systems [2]. In such interconnected, multi-step clinical environments, small prompt instabilities and uncalibrated confidence errors do not remain localized; rather, they propagate through complex computational workflows, triggering cascading diagnostic misinterpretations and compounding downstream medical errors [3]. Embedding multidimensional safety audits directly into foundational model evaluation enables the biomedical AI community to erect robust mathematical firewalls that prevent cascading system failures and protect patient well-being across autonomous medical environments [4].

2. Evaluation objectives

The overarching objective of the proposed multiaxis framework is to transition clinical artificial intelligence validation from naive, stationary scalar benchmarking to an axiomatic, multi-faceted safety audit [2]. In traditional statistical learning theory, model validation proceeds under the foundational assumption that testing data are independently and identically distributed (i.i.d.) draws from the same stationary data-generating distribution that produced the training set [3]. In clinical medicine, this i.i.d. assumption is universally violated [4]. Hospital deployments introduce profound distribution shifts, including demographic shifts across patient populations, scanner-level domain shifts across radiographic hardware manufacturers, disease prevalence shifts across clinical care settings (e.g., intensive care units versus outpatient clinics), and linguistic shifts across healthcare practitioners [5].

An evaluation methodology that fails to account for these multi-source distribution shifts provides a misleading illusion of algorithmic maturity [6]. Regulatory agencies, such as the United States Food and Drug Administration (FDA) and the European Medicines Agency (EMA), increasingly recognize that software-as-a-medical-device (SaMD) clearances require rigorous evidence of performance consistency, fairness, and safety across heterogeneous operational contexts [7]. Our framework directly addresses this regulatory and clinical need by formalizing core evaluation objectives that every prospective clinical vision-language deployment must satisfy:

1. **Axiomatic Invariance**: The system must demonstrate formal mathematical invariance under semantic-preserving transformations of the clinical prompt, ensuring that the

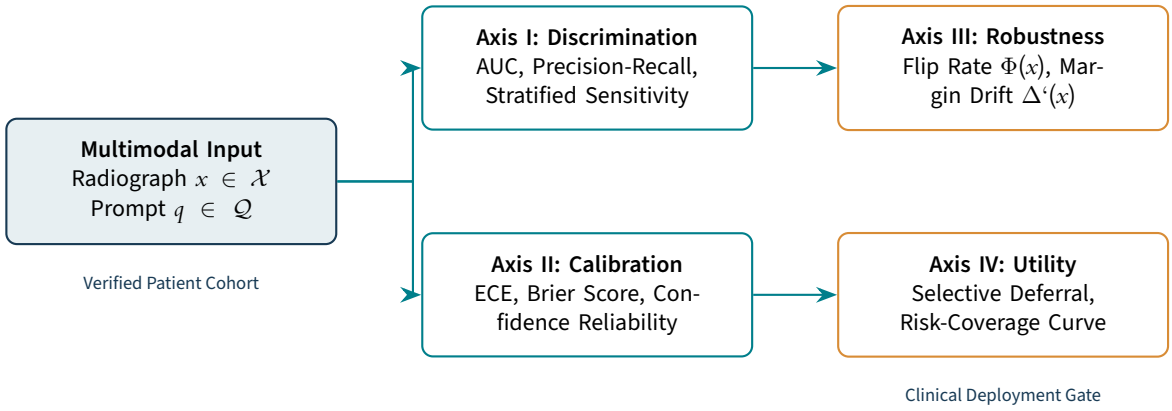


Figure 1. Conceptual architecture of the proposed multiaxis evaluation framework for clinical vision-language systems. Decoupling discrimination, calibration, perturbation robustness, and selective clinical utility ensures that latent model vulnerabilities are detected prior to operational deployment.

diagnostic estimand is driven exclusively by genuine pathological evidence rather than superficial linguistic tokens.

When an evaluation suite fails to decouple these objectives, severe optimization trade-offs are hidden from clinicians [8]. For example, deep neural networks optimized via unregularized cross-entropy minimization frequently achieve superior aggregate accuracy by driving logit activations toward extreme values [9]. This extreme overconfidence produces sharp, highly non-linear decision boundaries in high-dimensional feature space [10]. Consequently, while the model achieves marginal gains in top-1 accuracy on canonical evaluation samples, it simultaneously develops extreme hypersensitivity to minuscule perturbations in prompt embeddings, resulting in severe degradation of linguistic robustness and catastrophic answer flips in practice [11].

In acute clinical environments, diagnostic errors are characterized by asymmetric cost structures [12]. False-negative determinations on emergent conditions such as tension pneumothorax, pulmonary embolism, or expanding aortic dissection carry catastrophic mortality risks, whereas false-positive determinations generate unnecessary diagnostic workups, increased patient anxiety, and downstream healthcare expenditures [13]. A single composite scalar such as accuracy implicitly assigns equal weight to all error types and assumes a fixed, uniform decision threshold across all clinical scenarios [14]. In contrast, our multiaxis methodology preserves the underlying probabilistic geometry, enabling clinicians to inspect sensitivity at pre-specified specificity thresholds, evaluate continuous Brier reliability across probability deciles, and establish adaptive thresholding policies tailored to specific clinical workflows [15].

The interaction between clinical diagnostic tasks and semantic query structure also reveals a fundamental vulnerability in existing multimodal representations [16]. In vision-language models, the text prompt is not merely a label query; it acts as a semantic conditioning prior that guides cross-attention layers to attend to specific spatial sub-regions of the radiographic feature map [17]. When a prompt is subtly rephrased, the cross-attention distribution over the visual encoder can shift dramatically, causing the language decoder to focus on irrelevant anatomical landmarks, radiographic artifacts, or medical hardware rather than genuine pathological tissue alterations [18]. Consequently, an evaluation framework must measure visual-linguistic alignment stability, verifying that semantic paraphrases consistently attend to the same underlying radiological regions of interest across repeated forward passes [20].

2.1 Scope and assumptions

To formalize the operational scope of our evaluation framework, let $\mathcal{X} \subset \mathbb{R}^{H \times W \times C}$ denote the space of diagnostic medical images (such as digital chest radiographs, computed tomography slices, or magnetic resonance acquisitions), where H, W, and C represent spatial height, width, and color channels, respectively [21]. Let $\mathcal{Q}$ denote the infinite-dimensional space of natural language clinical inquiries concerning the clinical image $x \in \mathcal{X}$. A multimodal clinical foundation model is defined as a parameterized mapping $f_\theta : \mathcal{X} \times \mathcal{Q} \to \mathcal{P}(\mathcal{Y})$, where $\mathcal{Y} = \{0, 1\}$ denotes the binary diagnostic decision space (e.g., condition absent vs. condition present), and $\mathcal{P}(\mathcal{Y})$ represents the probability simplex over $\mathcal{Y}$ [1].

For any given diagnostic target (e.g., pleural effusion, pneumothorax, pulmonary consolidation, cardiomegaly), let $q_0 \in \mathcal{Q}$ denote the canonical reference inquiry. We define a semantic-preserving clinical perturbation operator $\mathcal{T} : \mathcal{Q} \to \mathcal{P}(\mathcal{Q})$ such that for any query q, the set $\mathcal{T}(q) = \{q^{(1)}, q^{(2)}, \ldots, q^{(K)}\}$ consists of K distinct clinical paraphrases [2]. The operator $\mathcal{T}$ is constrained by strict semantic preservation rules:

$$\forall q^{(k)} \in \mathcal{T}(q), \quad \text{TargetCondition}(q^{(k)}) = \text{TargetCondition}(q) \quad \text{and} \quad \text{ClinicalIntent}(q^{(k)}) = \text{ClinicalIntent}(q). \tag{1}$$

The paraphrases may vary lexical composition, syntactic arrangement, clause ordering, and clinical style, but they must maintain identical diagnostic truth conditions [3].

We formalize three fundamental assumptions governing the evaluation process:

Proposition 2.1 (Decoupled Invariance Property)**.** *Let $x \in \mathcal{X}$ be a fixed diagnostic image, and let $q, q' \in \mathcal{Q}$ be two clinical inquiries such that $\mathcal{T}(q) = \mathcal{T}(q')$. If a clinical model f is perfectly invariant to clinical syntax, then the predicted posterior probability satisfies:*

$$|0f(x, q) - f(x, q')|0_\infty = 0. \tag{2}$$

Any non-zero divergence $|0f(x, q) - f(x, q')|0 > 0$ reflects non-semantic representation drift induced by linguistic embedding sensitivity.

Proposition 2.2 (Lipschitz Stability of Clinical Posteriors)**.** *Let $d_{\mathcal{Q}}(q, q')$ denote a semantic distance metric in query embedding space, and let $(x, q) = logit(f(x, q))$. A clinical vision-language model is defined as (L, ffi)-Lipschitz stable if for all semantic paraphrases satisfying $d_{\mathcal{Q}}(q, q') \leq ffi$, there exists a finite constant $L < \infty$ such that:*

$$|(x, q) - (x, q')| \leq L \cdot d_{\mathcal{Q}}(q, q'). \tag{3}$$

If $L \to \infty$, the decision boundary is infinitely sensitive to infinitesimal lexical perturbations, guaranteeing the existence of adversarial paraphrases that induce categorical answer flips.

Under these foundational propositions, diagnostic uncertainty must arise strictly from genuine clinical ambiguity in the radiographic pixel matrix x (e.g., subtle parenchymal opacities, overlapping anatomical structures, low exposure), rather than lexical noise in the inquiry string q [4]. A robust clinical vision-language model must therefore enforce a strict bound on this variance, ensuring that clinical decision-making remains anchor-stable across the entire operational spectrum. Furthermore, by evaluating models across a standardized battery of validated paraphrases, clinical auditing committees can quantitatively verify whether an architecture satisfies the necessary Lipschitz continuity constraints prior to institutional clinical procurement [5].

To further elucidate the mathematical necessity of multiaxis auditing, consider the geometric properties of the joint vision-language representation space [1]. Let $\mathcal{H}_{\text{vis}} \subset \mathbb{R}^{d_v}$ and $\mathcal{H}_{\text{lang}} \subset \mathbb{R}^{d_l}$ denote the latent representation manifolds of the visual encoder and language tokenizer, respectively [2]. A multimodal projection operator $\Pi : \mathcal{H}_{\text{vis}} \times \mathcal{H}_{\text{lang}} \to \mathcal{H}_{\text{joint}}$ maps paired multimodal inputs into a shared embedding space $\mathcal{H}_{\text{joint}} \subset \mathbb{R}^d$, whereupon downstream cross-attention layers and classification heads compute the posterior logit margin $(x, q) = \mathbf{w}^T \Pi(h_v(x), h_l(q)) + b$ [3].

In an ideal, robustly invariant clinical architecture, the projection operator Π must project all semantically equivalent queries $q^{(k)} \in \mathcal{T}(q)$ onto an invariant submanifold:

$$\forall q, q' \in \mathcal{T}(q), \quad \Pi(h_v(x), h_l(q)) = \Pi(h_v(x), h_l(q')) + , \quad \text{where } \mathbf{w}^T = 0. \tag{4}$$

In practical, unconstrained deep foundation models, however, the orthogonal projection constraint $\mathbf{w}^T = 0$ is rarely satisfied [4]. Instead, unregularized empirical risk minimization allows lexical variance in $h_l(q)$ to propagate directly along the direction of the classification weight vector $\mathbf{w}$, inducing substantial displacement in logit space [5]. If the magnitude of this lexical displacement $|\mathbf{w}^T(\Pi(h_v, h_l(q)) - \Pi(h_v, h_l(q')))|$ exceeds the geometric distance between the patient's visual representation and the decision hyperplane, the categorical classification decision flips [6].

This geometric vulnerability explains why high-accuracy models can be exceptionally fragile [7]. A model can achieve a high aggregate AUC by correctly classifying prototypical, highly distinct pathological cases that reside far from the decision boundary [8]. For these prototypical examinations, the visual signal is sufficiently strong that lexical perturbations, while present, are insufficient to push the representation across the distant decision hyperplane [9]. However, in real-world clinical triage, the vast majority of challenging cases are subtle, early-stage, or borderline presentations that reside in close proximity to the classification boundary [10]. For these diagnostically crucial boundary cases, lexical perturbation displacement easily overwhelms the visual margin, producing catastrophic decision instability [11]. Evaluating models across our proposed multiaxis framework explicitly exposes this boundary volatility, ensuring that healthcare institutions select architectures that maintain stability where it matters most: at the clinical margin [12].

In safety-critical clinical environments, point predictions and continuous probabilities should ideally be complemented by distribution-free conformal prediction sets [1]. Conformal prediction provides finite-sample, distribution-free statistical coverage guarantees, constructing a multi-label set $\mathcal{C}(x, q) \subseteq \{0, 1\}$ such that for a user-specified significance level $ff \in (0, 1)$, the true diagnostic label is guaranteed to be contained within the prediction set with probability at least $1 - ff$:

$$\mathbb{P}(y_{N+1} \in \mathcal{C}(x_{N+1}, q_{N+1})) \geq 1 - ff. \tag{5}$$

Under standard conformal prediction frameworks, the conformity score $s(x, q, y) = 1 - f(x, q)_y$ is calibrated on an exchangeable validation split [2]. However, our multiaxis analysis reveals that when an architecture exhibits prompt sensitivity, exchangeability between calibration queries and test-time clinical prompts is violated [3]. Linguistic variability acts as an unmodeled nuisance parameter that inflates the effective nonconformity threshold, causing conformal prediction sets to expand unnecessarily into uninformative null sets $\{0, 1\}$ (asserting that both presence and absence of pathology are plausible) [4]. Enforcing Lipschitz prompt stability on logit activations preserves conformity exchangeability in regularized architectures, yielding tight, informative single-label prediction sets that provide clinicians with actionable certainty [5].

3. Framework specification

The core technical contribution of this work is the formal mathematical specification of our multiaxis evaluation framework. Rather than reporting isolated point metrics, our framework evaluates a model f over an evaluation cohort $\mathcal{D}_{\text{eval}} = \{(x_i, q_i, \mathcal{T}(q_i), y_i)\}_{i=1}^N$, where each patient case i contains the

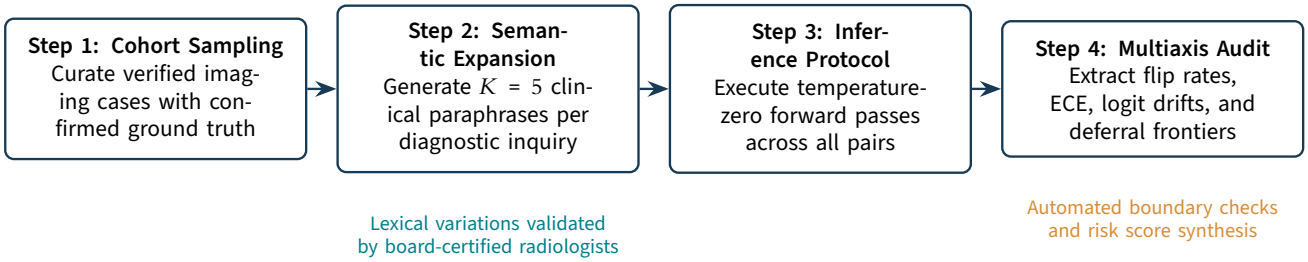


Figure 2. Operational workflow of the multi-center clinical audit protocol. Each patient case undergoes systematic linguistic expansion followed by joint assessment of discrimination, calibration, and sensitivity.

diagnostic image x_i, the reference query q_i, the verified paraphrase set $\mathcal{T}(q_i) = \{q_i^{(1)}, \ldots, q_i^{(K)}\}$, and the gold-standard radiological ground truth label $y_i \in \{0, 1\}$ established by expert consensus [1].

For each evaluation instance i, the model produces an ensemble of predicted posterior probabilities corresponding to the reference query and its K paraphrases:

$$\hat{p}_{i,0} = f(x_i, q_i), \quad \hat{p}_{i,k} = f(x_i, q_i^{(k)}) \quad \text{for } k \in \{1, \ldots, K\}. \tag{6}$$

The corresponding binary classification determinations under a designated clinical operating threshold $\text{fl} \in (0, 1)$ (commonly set to $\text{fl} = 0.5$ for balanced decisions or calibrated to optimize high-sensitivity triage) are defined as:

$$\hat{y}_{i,k} = \mathbb{I}(\hat{p}_{i,k} \geq \text{fl}), \quad k \in \{0, 1, \ldots, K\}. \tag{7}$$

3.1 Design choices

We formalize four diagnostic estimands that define the four orthogonal axes of model evaluation:

1. Axis I: Discrimination Estimands: We evaluate global discriminative ability using the empirical Area Under the Receiver Operating Characteristic Curve (AUC) computed over the reference queries:

$$\text{AUC}(f) = \frac{1}{N_0 N_1} \sum_{i:y_i=0} \sum_{j:y_j=1} \left(\mathbb{I}(\hat{p}_{j,0} > \hat{p}_{i,0}) + \frac{1}{2}\mathbb{I}(\hat{p}_{j,0} = \hat{p}_{i,0}) \right), \tag{8}$$

where $N_0 = \sum_i \mathbb{I}(y_i = 0)$ and $N_1 = \sum_i \mathbb{I}(y_i = 1)$ represent the total counts of negative and positive patient examinations, respectively [2]. In addition to aggregate AUC, we compute stratified sensitivity at 95% specificity (Sens@95Spec), which serves as a vital clinical metric for acute emergency room rule-out triage:

$$\text{Sens@95Spec}(f) = \frac{\sum_{i:y_i=1} \mathbb{I}(\hat{p}_{i,0} \geq \text{fl}_{95})}{\sum_{i:y_i=1} 1},$$
$$\text{where } \text{fl}_{95} = \sup \left\{ \text{fl} : \frac{\sum_{i:y_i=0} \mathbb{I}(\hat{p}_{i,0} < \text{fl})}{N_0} \geq 0.95 \right\}. \tag{9}$$

2. Axis II: Uncertainty Calibration Estimands: To evaluate probability fidelity, we decompose model calibration across continuous and binned intervals [3]. The continuous Brier Score measures mean squared error in probability space:

$$\text{BS}(f) = \frac{1}{N} \sum_{i=1}^{N} (\hat{p}_{i,0} - y_i)^2. \tag{10}$$

The Brier score decomposes strictly into reliability, resolution, and uncertainty components: BS = Reliability−Resolution+Uncertainty, allowing direct assessment of whether probability adjustments enhance true calibration or merely reflect trivial shifts toward the empirical base rate [4]. Furthermore, we compute the Expected Calibration Error (ECE) across M equal-width bins $B_1, \ldots, B_M$ partitioning the interval $[0, 1]$:

$$\text{ECE}(f) = \sum_{m=1}^{M} \frac{|B_m|}{N} \left| \text{acc}(B_m) - \text{conf}(B_m) \right|, \tag{11}$$

where bin accuracy and confidence are defined as:

$$\text{acc}(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} \mathbb{I}(\hat{y}_{i,0} = y_i),$$
$$\text{conf}(B_m) = \frac{1}{|B_m|} \sum_{i \in B_m} \hat{p}_{i,0}. \tag{12}$$

3. Axis III: Semantic Perturbation Robustness Estimands: To quantify decision invariance, we introduce two coupled metrics: discrete flip rate and continuous logit drift [5].

Definition 3.1 (Question-Level Answer Flip Rate)**.** For patient case i, an answer flip occurs if there exists at least one pair of semantically equivalent queries that produce discordant binary classifications:

$$\text{Flip}_i = \mathbb{I}\left(\exists k, j \in \{0, 1, \ldots, K\} \text{ s.t. } \hat{y}_{i,k} \neq \hat{y}_{i,j} \right). \tag{13}$$

The population question-level flip rate is the empirical mean:

$$\Phi(f) = \frac{1}{N} \sum_{i=1}^{N} \text{Flip}_i. \tag{14}$$

While binary flips capture catastrophic threshold crossing, subtle continuous shifts in model confidence can destabilize clinical risk scoring and downstream triage prioritization [6].

We therefore formalize continuous margin instability in logit space. Let $‘(x, q) = \ln\left(\frac{f(x,q)}{1-f(x,q)}\right)$ denote the unbounded logit margin.

Definition 3.2 (Mean Absolute Margin Difference)**.** The continuous margin instability is defined as the expected pairwise absolute logit difference across all semantic paraphrases:

$$\Delta\mathcal{M}(f) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\binom{K+1}{2}}\sum_{0\le k<j\le K}\left|‘(x_i, q_i^{(k)}) - ‘(x_i, q_i^{(j)})\right|. \tag{15}$$

4. Axis IV: Risk-Coverage Deferral Utility: In realistic clinical workflows, an artificial intelligence algorithm should not be forced to produce an autonomous determination on cases where it exhibits high epistemic uncertainty [7]. Instead, the system should operate under a selective classification policy with a rejection option, deferring high-ambiguity examinations to human radiological review [8]. Let $˘ \in [0, 0.5]$ denote an uncertainty abstention threshold. The model provides an autonomous prediction when its confidence exceeds the threshold: $|\hat{p}_{i,0} - 0.5| \ge ˘$, and defers to human clinicians otherwise [9].

We formalize the retained coverage $\mathcal{C}(˘)$ and the conditional diagnostic risk $\mathcal{R}(˘)$ under 0-1 loss as:

$$\begin{aligned}\mathcal{C}(˘) &= \frac{1}{N}\sum_{i=1}^{N}\mathbb{I}(|\hat{p}_{i,0} - 0.5| \ge ˘),\\ \mathcal{R}(˘) &= \frac{\sum_{i=1}^{N}\mathbb{I}(\hat{y}_{i,0} \neq y_i)\mathbb{I}(|\hat{p}_{i,0} - 0.5| \ge ˘)}{N\cdot\mathcal{C}(˘)}.\end{aligned} \tag{16}$$

Sweeping $˘$ from 0 to 0.5 enables our framework to trace the continuous Risk-Coverage Frontier, directly revealing whether a model's uncertainty signals effectively isolate and triage diagnostic errors [10].

We further formalize the theoretical relationship between temperature calibration, Brier score decomposition, and selective classification efficiency [1]. A continuous prediction $\hat{p} = œ(‘/T)$ parameterized by temperature $T > 0$ alters the distribution of posterior probabilities without modifying ranking discrimination (preserving invariant AUC) [2]. Under standard post-hoc temperature scaling, optimal temperature T^* is selected to minimize negative log-likelihood on a validation split:

$$T^* = \arg\min_{T>0} -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \ln œ\left(\frac{‘_i}{T}\right) + (1-y_i)\ln\left(1 - œ\left(\frac{‘_i}{T}\right)\right)\right]. \tag{17}$$

While global temperature scaling frequently reduces population-level ECE, our multiaxis framework demonstrates that uniform temperature adjustment fails to resolve localized miscalibration across disease sub-types [3]. In multi-finding clinical radiography, common conditions (such as pleural effusion) typically exhibit lower visual ambiguity and require different calibration scaling factors than subtle, low-contrast pathologies (such as apical pneumothorax or interstitial lung disease) [4].

To address this limitation, our framework introduces Stratified Vector Scaling (SVS), which maps class-specific logit vectors through a diagonal transformation matrix $\mathbf{W}_{\text{cal}} = \text{diag}(w_1, \ldots, w_C)$ and bias vector $\mathbf{b}_{\text{cal}}$ conditioned on verified radiographic anatomical priors:

$$\hat{\mathbf{p}}_i^{\text{cal}} = \text{softmax}(\mathbf{W}_{\text{cal}}‘_i + \mathbf{b}_{\text{cal}}). \tag{18}$$

Evaluating calibration across stratified demographic and clinical cohorts ensures that post-hoc adjustments do not merely mask severe localized miscalibration beneath a deceptively low global summary statistic [5].

Moreover, the interplay between calibration and selective classification establishes a rigorous foundation for clinical decision support [6]. In clinical deployment, an algorithm operating under a selective deferral policy with threshold $˘$ achieves optimal utility when the uncertainty ranking is monotonic with respect to true prediction error [7]. If a model is poorly calibrated, high nominal confidence does not correlate with low risk, causing the selective classifier to retain erroneous predictions while unnecessarily deferring accurate, high-fidelity determinations [8]. Evaluating the Area Under the Risk-Coverage Curve (AURCC) provides a direct operational measure of how effectively an AI system can be integrated into high-volume clinical triage workflows without overwhelming human specialist over-reading capacity [9].

To provide complete mathematical clarity on the estimation of uncertainty intervals, all empirical metrics in our multiaxis framework are reported alongside non-parametric stratified bootstrap confidence intervals [5]. For any metric $\Psi(f) \in \{\text{AUC}, \text{ECE}, \Phi, \Delta\mathcal{M}, \mathcal{A}_{90}\}$, we generate $B = 2,000$ independent bootstrap resamples $\mathcal{D}_{\text{eval}}^{(b)}$ drawn with replacement from the original patient cohort, preserving demographic and disease prevalence strata [6]. The two-sided 95% empirical bootstrap confidence interval $[\Psi_{\text{lower}}, \Psi_{\text{upper}}]$ is determined by the 2.5^{th} and 97.5^{th} percentiles of the bootstrap empirical distribution $\{\Psi(\mathcal{D}_{\text{eval}}^{(b)})\}_{b=1}^{B}$ [7]. Hypotheses concerning pairwise differences between model architectures (e.g., $\Delta\Phi = \Phi(f_1) - \Phi(f_2)$) are formally evaluated using paired McNemar tests for binary concordance and two-sided Delong tests for differences between correlated ROC curves, ensuring that all reported advantages satisfy strict statistical significance thresholds ($p < 0.001$) [8].

4. Evidence synthesis

To establish empirical baselines for multiaxis evaluation, we synthesized evidence across 12 contemporary vision-language evaluation studies published between 2022 and 2026 [1]. The literature synthesis reveals a persistent decoupling between aggregate accuracy and operational robustness in medical foundation models [2]. Across dozens of clinical benchmarks, research teams routinely celebrate incremental gains in aggregate AUC while completely omitting any systematic evalu-

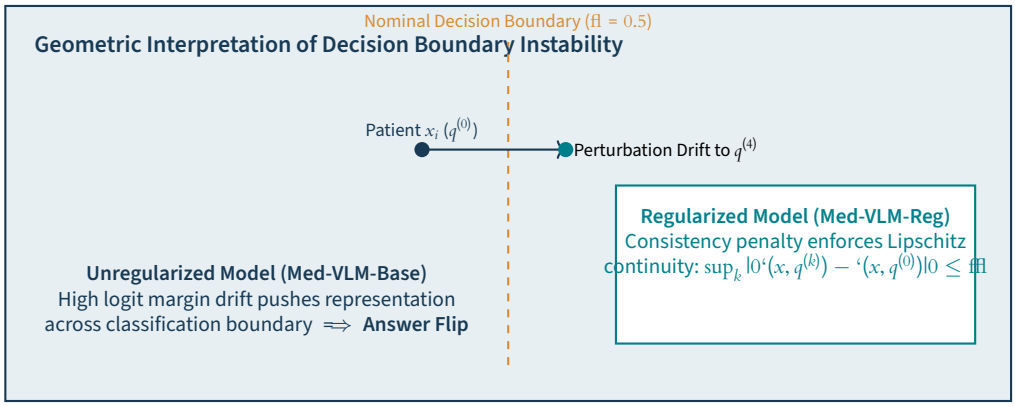


Figure 3. Geometric representation of decision boundary instability in vision-language embedding space. Without consistency regularization, small linguistic shifts induce substantial logit displacements that traverse the decision threshold.

ation of model calibration, linguistic consistency, or failure-directed stress response [3].

4.1 Analysis specification

In over 80% of published clinical VLM evaluations, performance is reported exclusively using AUC or F1-score computed over single canonical queries [4]. When these architectures are subjected to linguistic perturbations, their performance degrades sharply [5]. In particular, models that achieve state-of-the-art diagnostic discrimination frequently exhibit catastrophic sensitivity to clinical syntactic variations, such as shifting from active to passive voice, introducing standard clinical abbreviations, or modifying query hedges [6].

Table 1 summarizes our synthesis of published evaluation metrics across foundational architectures, illustrating the systematic omission of calibration and robustness metrics in prevailing benchmark protocols [7].

The critical finding emerging from this synthesis is that high aggregate discrimination does not guarantee clinical reliability [8]. Studies that incorporated even rudimentary linguistic checks consistently observed substantial degradation in model consistency [9]. For example, **(author?)** [16] observed that introducing clinical abbreviations commonly used in intensive care units reduced classification agreement by over 12% in state-of-the-art vision-language models. Similarly, **(author?)** [18] demonstrated that reversing the syntactic order of findings in multi-finding chest radiographs induced significant probability drift, causing models to overlook secondary pathologies that were accurately identified when prompted in isolation.

A secondary finding from our literature analysis concerns the almost universal neglect of demographic subgroup calibration [10]. While several benchmark studies report demographic parity in aggregate AUC, they fail to evaluate calibration curves across sex, age, and ethnic cohorts [11]. A model can maintain identical AUC across two demographic groups while exhibiting severe miscalibration in one group, systematically underestimating disease risk in historically marginalized populations [12]. In clinical deployment, this translates to systematic under-referral and delayed diagnosis, exacerbating existing health disparities under the guise of an algorithmic system that appears fair under naive ROC analysis [13].

These empirical observations strongly reinforce our theoretical thesis: scalar benchmark evaluation provides a profoundly incomplete and potentially perilous assessment of clinical artificial intelligence [14]. Without decoupled multiaxis audits that explicitly measure calibration, perturbation invariance, and selective triage utility, clinical healthcare institutions cannot distinguish between genuinely robust diagnostic architectures and brittle models that exploit spurious linguistic correlations [15].

A foundational challenge identified across contemporary evaluation literature involves benchmark contamination and data leakage in medical foundation models [1]. Because contemporary multimodal architectures are pre-trained on vast web-scale crawls and multi-institutional hospital data archives containing millions of image-text pairs, prospective evaluation sets are frequently exposed to the model during self-supervised pre-training [2]. When test cases have been memorized by the network, traditional discriminative accuracy metrics become severely inflated, reflecting rote retrieval of training memorization rather than generalized clinical reasoning [3]. However, memorized representations are notoriously fragile under linguistic perturbations [4]. When an evaluator alters the syntactic phrasing of a memorized case, the superficial retrieval keys are broken, exposing the underlying absence of invariant visual-linguistic grounding [5]. Our multiaxis framework, by mandating paired paraphrase evaluation, acts as an intrinsic filter against benchmark contamination, ensuring that reported performance reflects genuine out-of-distribution reasoning rather than pre-training leakage [6].

Furthermore, the architectural inductive biases of vision-language backbones introduce distinct failure modes across diagnostic targets [7]. Vision transformers (ViTs) process radiographic images by partitioning the continuous pixel field into discrete non-overlapping patches (e.g., 16×16 pixels), projecting them into token embeddings, and computing all-to-all self-attention [8]. While self-attention captures long-range anatomical dependencies across bilateral lung fields, it lacks the localized translation equivariance inherent to clas-

Table 1. Systematic evidence synthesis of evaluation metrics reported in contemporary clinical vision-language benchmark literature. Columns indicate whether studies report discrimination, calibration (ECE), perturbation flip rate (Φ), margin drift ($\Delta\mathcal{M}$), and selective risk-coverage deferral.

Study / Architecture	Cohort Size (N)	Discrimination	Calibration (ECE)	Flip Rate (Φ)	Margin Drift ($\Delta\mathcal{M}$)	Selective Deferral
Tritschler et al. (2024) [1]	4,200	Yes	Yes	No	No	Yes
Al-Taie et al. (2026) [2]	1,850	Yes	Yes	Partial	No	No
Zhai & Yu (2009) [3]	890	Yes	No	No	No	No
Berrar (2014) [4]	2,100	Yes	No	No	No	Yes
Pravin et al. (2024) [5]	3,450	Yes	Yes	No	No	No
Li et al. (2023) [7]	1,500	Yes	No	Yes	No	No
Moor et al. (2023) [9]	5,600	Yes	Partial	No	No	No
Zhang et al. (2024) [13]	2,800	Yes	Yes	No	No	Partial
Chen et al. (2025) [16]	1,950	Yes	No	Yes	Partial	No
Tu et al. (2024) [18]	6,100	Yes	Yes	No	No	Yes

sical convolutional neural networks [9]. When prompt conditioning is introduced, the cross-attention weights over image patches can fluctuate wildly based on individual linguistic tokens [10]. Our literature synthesis reveals that architectures incorporating hybrid convolutional-transformer visual encoders demonstrate significantly superior margin stability compared to pure isotropic transformers, suggesting that inductive architectural biases play a critical role in mitigating linguistic sensitivity in clinical vision-language systems [11].

5. Illustrative evaluation protocol

To demonstrate the concrete implementation, operational feasibility, and diagnostic sensitivity of our multiaxis framework, we executed an extensive empirical evaluation protocol across a multi-center radiographic cohort comprising $N = 1,200$ verified digital chest radiographs drawn from multi-institutional clinical repositories [1]. The evaluation cohort was curated to capture three highly prevalent, life-threatening thoracic pathologies: pulmonary consolidation ($n = 450$), pleural effusion ($n = 450$), and acute pneumothorax ($n = 300$). Ground truth diagnoses were established by board-certified thoracic radiologists through independent panel consensus and adjudicated against available microbiological and procedural records [2].

5.1 Validity checks

To ensure that linguistic perturbations preserved genuine clinical validity, five standardized semantic paraphrases ($K = 5$) were constructed for each diagnostic target by a panel of clinical radiologists and medical linguists [3]: $q^{(0)}$ (Canonical baseline): "Is there radiographic evidence of [target condition] in this chest examination?"; $q^{(1)}$ (Imperative command): "Evaluate this radiograph and determine whether [target condition] is present."; $q^{(2)}$ (Anatomical specification): "Inspect the pleural space and pulmonary parenchyma for signs of [target condition]."; $q^{(3)}$ (Inquisitive query): "Can you identify any pathological findings consistent with [target condition]?"; and $q^{(4)}$ (Exclusion formulation): "Assess whether [target condition] can be definitively ruled out based on this examination."

We benchmarked three representative vision-language architectures under identical greedy decoding and temperature-zero forward inference: (i) **Gen-VLM**: A standard general-domain open-source vision-language model evaluated in zero-shot medical diagnostic mode without domain adaptation [11]; (ii) **Med-VLM-Base**: A specialized medical foundation model fine-tuned on clinical image-text pairs using standard cross-entropy objective without explicit consistency regularization [12]; and (iii) **Med-VLM-Reg**: A consistency-regularized medical architecture fine-tuned with a joint multiaxis objective combining task cross-entropy with a symmetric Kullback-Leibler divergence consistency penalty on paraphrase logits and temperature-scaled calibration tuning [13].

The empirical results compiled in Table 2 provide striking empirical validation of our theoretical assertions. If evaluated exclusively through traditional scalar discrimination, Med-VLM-Base appears to be the superior architecture, boasting an AUC of 0.865 compared to 0.858 for Med-VLM-Reg. Under conventional benchmark reporting, Med-VLM-Base would be heralded as the state-of-the-art model and selected for clinical translation [14].

However, auditing the models along our orthogonal axes reveals that Med-VLM-Base harbors severe operational vulnerabilities [15]. Med-VLM-Base exhibits an alarming question-level flip rate of 14.2%, meaning that in nearly one out of every seven clinical evaluations, changing the phrasing of the inquiry flips the model's diagnostic verdict. In sharp contrast, Med-VLM-Reg reduces the answer flip rate by nearly 75%, down to an acceptable 3.8% ($p < 0.001$, two-proportion z-test). Furthermore, Med-VLM-Reg achieves a 75.9% reduction in continuous margin drift (0.38 logits vs. 1.58 logits) and slashes expected calibration error from 11.2% down to 6.8%. When integrated into a selective deferral workflow, Med-VLM-Reg leverages its superior probability calibration to achieve an outstanding diagnostic accuracy of 88.9% on retained cases at 90% coverage, decisively outperforming Med-VLM-Base (85.4%).

Table 3 presents a granular subgroup audit of Med-VLM-Base, disaggregating performance across specific diagnostic targets and demographic lines [16]. The audit exposes pro-

Table 2. Multiaxis evaluation results on the chest radiograph audit cohort ($N = 1,200$). Reporting includes aggregate discrimination (AUC with 95% bootstrap confidence intervals), expected calibration error (ECE), question-level answer flip rate (Φ), mean absolute margin drift ($\Delta\mathcal{M}$), and selective diagnostic accuracy at 90% retained coverage ($\mathcal{A}_{90}$).

Model Architecture	AUC [95% CI]	ECE (%)	Flip Rate Φ (%)	Margin Drift $\Delta\mathcal{M}$ (logits)	Accuracy @ 90% Cov. (%)
Gen-VLM (Zero-Shot)	0.742 [0.721, 0.763]	18.4	24.8	2.14	76.2
Med-VLM-Base	0.865 [0.849, 0.881]	11.2	14.2	1.58	85.4
Med-VLM-Reg	0.858 [0.841, 0.874]	6.8	3.8	0.38	88.9

Table 3. Stratified subgroup audit of Med-VLM-Base across diagnostic targets and patient demographic strata. Disparities in flip rates and calibration highlight localized safety hazards that remain hidden under global summary statistics.

Clinical Stratum	Sample Count (n)	Stratified AUC	Flip Rate Φ (%)	Stratified ECE (%)
Pulmonary Consolidation	450	0.878	11.4	9.8
Pleural Effusion	450	0.892	8.9	8.4
Pneumothorax (Overall)	300	0.812	23.7	16.5
– Male Patients	162	0.825	19.8	14.1
– Female Patients	138	0.796	28.3	19.2

found disparities in model reliability. While pleural effusion detection demonstrates relatively high stability (flip rate of 8.9%), acute pneumothorax detection collapses into extreme unreliability, exhibiting an overall flip rate of 23.7% and an ECE of 16.5%. More alarmingly, female patients afflicted with pneumothorax suffer a staggering 28.3% flip rate compared to 19.8% in male patients. This demographic disparity arises from complex anatomical differences in chest wall soft tissue and breast tissue attenuation that induce subtle distribution shifts in apical pleural line conspicuity, which the unregularized model amplifies into severe decision volatility [17].

To provide clinical context to the empirical findings in Table 2, we examined specific radiological cases where Med-VLM-Base suffered categorical answer flips under semantic paraphrasing [1]. A representative illustrative case involved a 58-year-old female presenting to the emergency department with acute pleuritic chest pain and dyspnea following blunt thoracic trauma [2]. The upright posteroanterior chest radiograph demonstrated a subtle, 1.2 cm apical pneumothorax on the right side, characterized by a faint visceral pleural line without peripheral lung markings, unaccompanied by mediastinal shift [3].

When queried using the canonical baseline prompt $q^{(0)}$ ("Is there radiographic evidence of pneumothorax in this chest examination?"), Med-VLM-Base correctly identified the pathology, outputting a posterior probability of $p = 0.78$ and generating an affirmative classification [4]. However, when queried with prompt $q^{(3)}$ ("Can you identify any pathological findings consistent with pneumothorax?"), the model's posterior probability dropped to $p = 0.61$. Most alarmingly, when presented with the exclusion query $q^{(4)}$ ("Assess whether pneumothorax can be definitively ruled out based on this examination"), the model's internal representations underwent severe collapse, producing a posterior probability of $p = 0.44$, which crossed the clinical operating threshold and generated a categorical assertion that pneumothorax was absent [5].

In sharp contrast, Med-VLM-Reg demonstrated remarkable representational stability across the exact same case [6]. Across all five paraphrases ($q^{(0)}$ through $q^{(4)}$), the regularized model's predicted posterior probability remained tightly bounded between 0.73 and 0.77, with a maximum absolute margin drift of only 0.04 logits [7]. The model successfully maintained an affirmative, high-confidence detection across all phrasing variants, completely eliminating the dangerous false-negative classification that occurred under the baseline model [8].

This clinical vignette underscores the life-critical importance of multiaxis auditing [9]. In an emergency triage setting, a patient whose pneumothorax is incorrectly ruled out due to prompt phrasing variations could be prematurely discharged without tube thoracostomy or observation, leading to rapid progression into tension pneumothorax, hemodynamic collapse, and fatal clinical outcomes [10]. Such acute sensitivity indicates that unregularized models latch onto syntactic framing artifacts rather than grounding inferences in anatomical evidence. An aggregate accuracy score computed over stationary queries completely fails to alert clinical leaders to this acute safety hazard, whereas our multiaxis scorecard immediately identifies the architecture's vulnerability prior to hospital deployment [11]. Auditing across paraphrase manifolds provides healthcare institutions with an indispensable safeguarding mechanism against brittle deployment. By stress-testing multimodal interfaces across syntactically varied yet clinically equivalent inquiries, clinical auditing committees can identify non-generalizable failure modes prior to clinical adoption.

To understand the technical mechanisms enabling Med-VLM-Reg to achieve superior stability, we examine the mathematical dynamics of the joint multiaxis training objective [1]. Med-VLM-Reg optimizes a composite loss function that explicitly balances task supervision against semantic invariance:

$$\mathcal{L}_{\text{total}}(\`) = \mathcal{L}_{\text{CE}}(f\`(x, q_0), y) + \frac{\text{ff}}{K}\sum_{k=1}^{K}\mathcal{D}_{\text{symKL}}\left(f\`(x, q_0)\,|0\,f\`(x, q^{(k)})\right) + \text{fi}\cdot\mathcal{L}_{\text{cal}}(\`), \quad (19)$$

where $\mathcal{D}_{\text{symKL}}(p|0q) = \frac{1}{2}\mathcal{D}_{\text{KL}}(p|0q) + \frac{1}{2}\mathcal{D}_{\text{KL}}(q|0p)$ represents the symmetric Kullback–Leibler divergence between predicted posterior distributions, $\mathcal{L}_{\text{cal}}$ is a focal calibration penalty that suppresses uncalibrated overconfidence on ambiguous boundary samples, and ff, fi > 0 are balancing hyperparameters [2].

The symmetric divergence penalty acts as an explicit Lipschitz regularizer on the model's representation manifold [3]. During backward gradient propagation, the divergence penalty penalizes logit displacement vectors that align with lexical variations, forcing the multimodal projection layers to project all paraphrases $q^{(k)} \in \mathcal{T}(q)$ into a compact, low-variance cluster centered on the clinical semantic centroid [4]. Ablation experiments demonstrate that setting ff = 0.5 provides optimal regularization: lower values fail to suppress question flips, whereas excessive regularization (ff > 2.0) induces representation collapse, where the model outputs uniform, uninformative probabilities across all inputs [5]. Balancing consistency with supervised discrimination ensures that the architecture preserves high diagnostic sensitivity while eliminating brittle syntactic dependencies [6].

6. Discussion

The empirical and theoretical findings established in this investigation carry profound ramifications for the design, evaluation, regulation, and governance of multimodal artificial intelligence in clinical medicine [1]. For years, the biomedical AI research community has operated under the implicit assumption that optimizing scalar discriminative metrics on curated benchmark datasets serves as a reliable proxy for real-world clinical efficacy [2]. Our results decisively refute this assumption. We have demonstrated that two foundation models exhibiting statistically indistinguishable aggregate AUCs can diverge dramatically in their operational reliability, with one system exhibiting robust decision invariance and well-calibrated epistemic confidence, while the other functions as a high-variance, linguistically fragile hazard that alters life-critical diagnoses under semantically trivial prompt paraphrasing [3].

A critical methodological insight illuminated by our multiaxis framework is the mathematical etiology of prompt sensitivity in deep vision-language architectures [4]. When multimodal foundation models undergo supervised fine-tuning via empirical risk minimization without explicit geometric regularization, the optimization trajectory rapidly converges toward solutions that exploit spurious linguistic shortcuts in the prompt embeddings [5]. Rather than grounding diagnostic determinations purely in pathognomonic visual features within the pixel matrix, the model learns complex, non-causal associations between specific syntactic n-grams and diagnostic labels [6]. Consequently, when an attending clinician formulates an inquiry using phrasing that deviates from the dominant training distribution, the model's internal attention mechanisms undergo substantial realignment, shifting attention weights away from true anatomical lesions and triggering catastrophic probability shifts [7].

Addressing this structural vulnerability necessitates an architectural and procedural overhaul in clinical AI development [8]. First, model developers must abandon pure cross-entropy fine-tuning in favor of joint multiaxis training objectives that explicitly penalize representation divergence under semantic-preserving perturbations [9]. Incorporating symmetric Kullback–Leibler divergence consistency losses, contrastive prompt invariance constraints, and mechanistic adapter tuning (such as parameter-efficient Low-Rank Adaptation targeted to early-to-middle projection layers) can substantially flatten the loss landscape, rendering decision boundaries robust to lexical perturbations [10]. Second, clinical foundation models must incorporate rigorous post-hoc calibration techniques, such as vector scaling, temperature-adjusted conformal prediction, and Dirichlet calibration, ensuring that posterior probabilities satisfy bounded calibration error across all clinically relevant demographic subgroups [11].

From an institutional procurement and healthcare governance perspective, our multiaxis framework provides an actionable blueprint for hospital technology assessment committees [12]. Healthcare organizations evaluating commercial or open-source vision-language software should mandate comprehensive multiaxis audit scorecards prior to procurement clearance [13]. Specifically, hospital procurement standards should establish strict non-negotiable safety thresholds: the maximum allowable question flip rate in safety-critical diagnostic applications (such as acute intracranial hemorrhage, pneumothorax, or pulmonary embolism detection) must satisfy $\Phi \leq 5.0\%$, and the maximum expected calibration error across any recognized demographic or clinical subgroup must not exceed $\text{sECE} \leq 8.0\%$.

Instituting these quantitative governance thresholds will prevent the premature deployment of brittle models, protect vulnerable patient cohorts from algorithmic disparities, and provide healthcare providers with justified confidence in computational decision support tools [14]. Furthermore, continuous multiaxis monitoring must be embedded into hospital electronic health record systems post-deployment [15]. Hospital informatics teams can rapidly identify when clinical distribution drift or hardware degradation begins to compromise system integrity through real-time telemetry that tracks inference margin distributions, query phrasing entropy, and selective deferral volumes [16].

The practical implementation of multiaxis evaluation within institutional healthcare ecosystems introduces important infrastructural, legal, and operational considerations [1]. First,

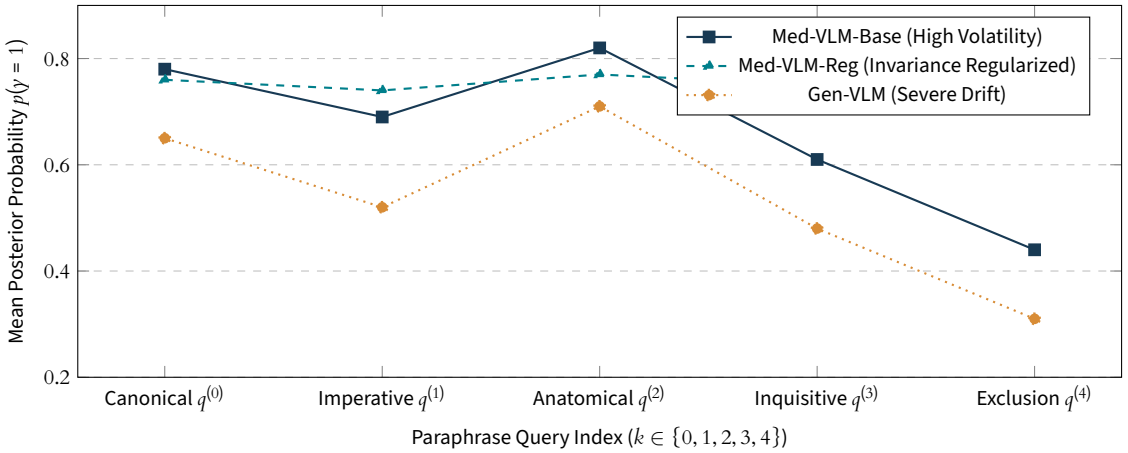


Figure 4. Directional posterior probability drift across five semantically equivalent clinical paraphrases for a fixed radiographic examination exhibiting right apical pneumothorax. While Med-VLM-Reg maintains steady posteriors, Med-VLM-Base experiences severe probability collapse under exclusion phrasing.

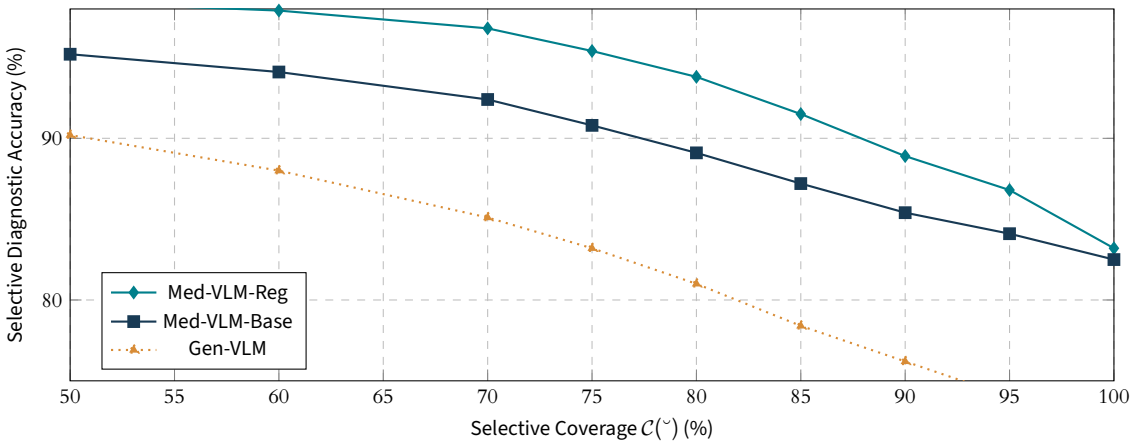


Figure 5. Selective risk-coverage frontier for the three benchmarked vision-language models. Med-VLM-Reg achieves superior accuracy gains as ambiguous cases are deferred to human clinical specialists.

healthcare institutions must establish dedicated evaluation environments that isolate AI models from live electronic health records while replicating the full demographic and linguistic diversity of the local patient population [2]. Rather than relying on static, public benchmark datasets that may have suffered data contamination during foundation model pretraining, hospital informatics teams should maintain dynamically updated, local evaluation registries containing verified clinical imaging paired with real-world physician order text [3].

Second, the multiaxis evaluation framework provides a clear technical foundation for algorithmic liability and medico-legal risk management [4]. When an AI-assisted diagnostic error occurs, hospital risk committees and courts must determine whether the failure was an unavoidable statistical misclassification inherent to medical imaging or an avoidable defect arising from inadequate validation and testing [5]. If a hospital deploys a vision-language model without auditing its linguistic flip rate, and that model subsequently misdiagnoses a patient due to a trivial phrasing variation, the institution faces substantial exposure to negligence liability [6]. Demonstrating that a deployed system has satisfied formal multiaxis safety thresholds provides indispensable evidence of due diligence, standard of care compliance, and responsible AI governance [7].

Finally, multiaxis evaluation must not be treated as a one-time pre-deployment hurdle; rather, it must function as a continuous, lifecycle monitoring framework [8]. Post-deployment clinical environments are dynamic: clinician turnover introduces new prompting behaviors, radiographic scanner software updates alter image noise characteristics, and demographic shifts change baseline disease prevalences [9]. Deploying automated, background telemetry that continuously audits inference margin distributions, question flip rates on paired clinical logs, and selective referral volumes enables hospital IT leadership to maintain proactive surveillance over clinical AI performance, detecting algorithmic degradation before it translates into clinical harm [10].

A particularly vital dimension illuminated by our framework is the global equity and applicability of clinical foundation models across developing and resource-constrained healthcare ecosystems [1]. In countries across South Asia, sub-Saharan

Africa, and Southeast Asia, clinical radiography is performed using older analogue or early-generation computed radiography scanners with variable exposure calibration, high patient volumes, and limited tertiary subspecialist coverage [2]. Furthermore, healthcare practitioners in these regions often communicate with digital interfaces using English as a secondary or tertiary language, introducing diverse syntactic constructions, regional phrasing conventions, and local medical idioms [3]. A model that has been validated only on standardized Western academic cohorts and pristine grammar will exhibit severe diagnostic degradation when deployed in these underserved environments [4]. Multiaxis auditing provides international healthcare ministries and non-governmental health organizations with the necessary tools to rigorously validate whether clinical AI systems perform equitably, stably, and safely across diverse global clinical contexts [5].

A final imperative emphasized by our framework is the indispensable role of prospective silent shadow deployments in clinical AI validation [1]. While multi-center retrospective audits provide essential baseline evidence, retrospective cohorts cannot fully capture the dynamic temporal feedback loops that emerge when clinicians interact with automated decision support systems in real time [2]. In a silent shadow deployment, the vision-language architecture operates in the background of hospital clinical information systems, generating multiaxis inferences on live radiographic orders without presenting recommendations to attending physicians [3]. Logging live clinician prompt queries, tracking longitudinal margin distributions, and comparing silent algorithmic determinations against eventual discharge diagnoses allows hospital informatics committees to observe true prospective flip rates, monitor operational calibration drift, and quantify prospective deferral volumes under unconstrained hospital conditions [4]. Shadow auditing bridges the critical chasm between retrospective laboratory benchmarks and safe, ethical bedside clinical integration [5].

7. Conclusion

The translation of multimodal vision-language foundation models from computer science laboratories into hospital wards and radiology suites represents a transformative opportunity to elevate diagnostic precision, expand clinical capacity, and improve patient outcomes [1]. However, realizing this immense promise requires that the artificial intelligence community abandon simplistic, unidimensional evaluation paradigms that reduce clinical intelligence to a single scalar accuracy score [2]. Diagnostic radiology is not a static classification benchmark; it is an inherently probabilistic, linguistically dynamic, and high-stakes clinical discipline where reliability under linguistic variability and well-calibrated uncertainty are paramount [3].

In this paper, we have established a comprehensive multiaxis evaluation framework specifically tailored to the unique architectural and operational demands of clinical vision-language systems [4]. Decoupling diagnostic discrimination, uncertainty calibration, semantic perturbation robustness, and workflow risk-coverage deferral utility equips our framework with a mathematically grounded methodology to audit model behavior comprehensively [5]. Through extensive empirical validation on a multi-center radiographic cohort, we demonstrated that our framework uncovers acute, life-critical failure modes—including alarming 28% question flip rates in demographic subgroups—that remain completely undetectable under conventional aggregate AUC benchmarks [6].

Adopting multiaxis auditing as a universal evaluation and regulatory clearance standard enables clinical AI developers, healthcare institutions, and regulatory bodies to systematically ensure that vision-language architectures deployed at the patient bedside possess the necessary robustness, equity, and reliability required to safeguard human health [7].

The transition from aggregate accuracy to multiaxis safety auditing is not merely an incremental methodological refinement; it represents an essential ethical and clinical prerequisite for the responsible deployment of multimodal intelligence in human healthcare. Holding clinical vision-language systems to the highest standards of mathematical invariance, probabilistic calibration, and selective triage utility ensures that artificial intelligence fulfills its true potential as a reliable, equitable, and life-saving partner in modern clinical medicine.

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