A Latent Diffusion Framework for Generating Counterfactual Radiographs to Disentangle Visual Grounding from Lexical Invariance in Multimodal Diagnosis

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ABSTRACT Multimodal foundation models deployed for medical visual question answering frequently rely on superficial linguistic correlations rather than genuine anatomical visual evidence. When clinical questions undergo syntactic paraphrasing, contemporary architectures alter diagnostic conclusions in over thirty percent of cases, revealing severe epistemic fragility. However, auditing whether these diagnostic flips stem from visual grounding failure or language prior bias remains fundamentally constrained by observational medical datasets, where pathological findings cannot be causally manipulated independently of patient anatomical confounders. To resolve this empirical bottleneck, this investigation introduces a mask-guided latent diffusion framework designed to synthesize high-fidelity counterfactual chest radiographs. Our architecture formulates a localized reverse stochastic differential equation trajectory modulated by cross-attention pathology steering and structural structural-similarity regularization, enabling precise surgical insertion and removal of focal thoracic lesions while strictly preserving underlying patient identity and bony morphology. Using this generative engine, we construct a certified benchmark suite comprising 4,000 paired observational-counterfactual radiographs across pneumothorax, pleural effusion, and cardiomegaly. Multi-reader clinical Turing audits by board-certified radiologists demonstrate 94.2% structural realism, confirming that synthetic modifications remain indistinguishable from authentic physiological presentations. Systematic stress-testing of nine prominent vision-language models across factual and counterfactual pairs demonstrates that language shortcuts account for 68.4% of observed paraphrase flips. Counterfactual preference tuning reduces prompt sensitivity by 84.1% while elevating true visual grounding alignment, providing a reproducible audit protocol for pre-market algorithmic safety certification.

1. Causal Disentanglement Bottlenecks in Observational Medical VQA

1.1. The Illusion of Visual Grounding in Healthcare Foundation Models

As rigorously demonstrated in the foundational benchmark established by Sadanandan and Behzadan [1], contemporary medical vision-language foundation models exhibit alarming behavioral fragility under syntactic query reformulations. While multimodal deep learning architectures have demonstrated astonishing capabilities in medical visual question answering (VQA), often achieving near-radiologist performance on canonical diagnostic benchmarks [2], their clinical reliability remains profoundly compromised by an over-reliance on superficial linguistic priors. Foundation models combining autoregressive transformer decoders with deep visual encoders generate comprehensive radiographic narratives, answer intricate clinical queries, and detect subtle parenchymal abnormalities [3]. Despite these high benchmark metrics, recent critical audits reveal that foundation models frequently operate as sophisticated statistical text

predictors rather than grounded visual interpreters [4]. When presented with identical thoracic radiographs, minor lexical substitutions, clinical shorthand variations, or syntactic rephrasings in the diagnostic inquiry cause state-of-the-art models to abruptly contradict their own diagnostic predictions [5].

In their comprehensive multi-center evaluations across MIMIC-CXR, PadChest, and VinDr-CXR, Sadanandan and Behzadan [1] documented that minor prompt paraphrasing alters diagnostic decisions in up to 35% of clinical cases, uncovering an acute disconnect between benchmark scores and genuine visual reasoning. Their empirical investigations established that token-level attention distributions within intermediate transformer cross-attention layers frequently decouple from pathological visual regions, gravitating instead toward salient syntactic tokens in the inquiry string. Consequently, when clinicians pose equivalent inquiries using conversational rather than canonical phrasing, cross-modal attention maps disperse across clinically irrelevant background anatomy. This observation exposes a profound epistemic vulnerability: traditional static benchmarks reward models for memorizing co-occurrence statistics between standard prompt templates and common clinical findings, masking severe underlying sensitivity to language variance. Resolving this critical diagnostic dilemma requires moving beyond observational evaluation suites toward causal frameworks that can isolate whether prediction flips originate from genuine failures of visual feature extraction or opportunistic exploitation of textual shortcuts.

This behavioral volatility indicates a fundamental flaw in how multimodal networks integrate visual evidence with textual context [6]. In high-stakes clinical workflows, a diagnostic decision support tool must anchor its conclusions to objective physical findings—such as visceral pleural lines, consolidation opacities, or cardiothoracic ratio measurements—rather than syntactic phrasing idiosyncrasies [7]. If a system diagnoses a pneumothorax under direct phrasing but denies the condition when asked using conversational clinical shorthand, healthcare providers cannot determine whether the network failed to visually ground the pathology or succumbed to linguistic shortcut bias [8].

Standard evaluation protocols fail to detect this failure mode because they evaluate models on static test splits where each radiograph is paired with a single canonical question [9]. In real-world emergency departments and intensive care units, physicians formulate inquiries with significant linguistic diversity [10]. Variations in regional dialects, level of clinical seniority, and keyboard input speeds produce disparate syntactic structures for identical diagnostic concepts [11]. When models exhibit high accuracy on fixed templates but collapse under linguistic permutations, their clinical utility is severely compromised [12].

1.2. The Confounding Nature of Observational Radiographic Cohorts

The fundamental obstacle to resolving this dilemma resides in the nature of observational clinical data [13]. Contemporary medical AI benchmarking relies almost exclusively on retrospective observational datasets, such as MIMIC-CXR, PadChest, and VinDr-CXR [14]. In observational cohorts, pathological manifestations are inextricably entangled with patient-specific anatomical characteristics, demographic co-factors, imaging equipment parameters, and disease co-morbidities [15]. For instance, cardiomegaly predominantly appears in elderly patients exhibiting chronic pulmonary vascular redistribution, tortuous thoracic aortas, and degenerative osteophytosis [16].

Consequently, vision-language models exploit these unobserved visual and textual correlations as predictive shortcuts [17]. When queried about cardiac enlargement, a network may base its prediction on peripheral spinal degenerations or catheter placements rather than genuine ventricular diameter enlargement [18]. In observational data, one cannot hold patient anatomy perfectly constant while selectively intervening on a single pathological feature [19]. As emphasized by Sadanandan and Behzadan [1], observational benchmarking intrinsically conflates syntactic prompt sensitivity with patient-level radiographic variance, because natural disease progression alters lung inflation, vascular caliber, and patient positioning between consecutive acquisitions. Disentangling true visual grounding from linguistic shortcutting therefore demands a causal intervention paradigm: observing how a model prediction changes when a specific pathological lesion is surgically added to or removed from an otherwise invariant radiographic anatomy [20].

1.3. Radiographic Physics and Projection Geometry Confounders

The physical formation of projection radiographs complicates observational causal analysis [21]. A chest radiograph is a two-dimensional summation of all anatomical structures along the path of the X-ray beam [22]. Differences in patient positioning (posteroanterior versus anteroposterior), focal spot-to-detector distance, and respiratory inspiratory effort fundamentally alter thoracic geometry [23]. In shallow inspiration, the heart appears spuriously enlarged and basal pulmonary bronchovascular markings crowd together, mimicking congestive heart failure or basilar consolidation [24].

In observational datasets, pairs of radiographs taken from the same patient across different hospital visits inevitably differ in inspiration, rotation, and exposure calibration [25]. These technical discrepancies introduce massive visual domain shifts that dwarf subtle pathological differences [26]. Consequently, comparing two different observational radiographs of the same patient cannot isolate the causal effect of pathology on model reasoning [27]. Generative counterfactual synthesis provides the only viable methodology for establishing true causal experimental controls: modifying the pathology in the digital latent space while holding all projection geometry, patient habitus, and bony anatomy mathematically invariant [28].

1.4. Selection Bias and Hospital Referral Artifacts in Clinical Archives

Observational medical archives embody severe institutional selection mechanisms that distort multimodal learning distributions. Patients imaged in acute tertiary trauma centers present with high baseline pre-test probabilities of urgent thoracic emergencies, including tension pneumothoraces, hemothoraces, and

rib fractures. Frequently, these urgent radiographs already display therapeutic hardware interventions, such as large-bore thoracostomy chest tubes, endotracheal tubes, or central venous catheters.

Multimodal foundation models trained on uncurated hospital datasets inadvertently learn spurious statistical dependencies between these therapeutic artifacts and diagnostic text labels. When an automated model is queried about a pneumothorax, it often scans the lateral chest wall for chest tube insertion sites rather than examining the pleural apex for visceral pleural line displacement. When an inquiry is rephrased into conversational syntax, the model's text-to-vision attention weights shift away from the chest tube artifact, causing an immediate diagnostic answer flip. Observational test cohorts cannot expose this flawed shortcut because chest tubes and pneumothoraces co-occur with high statistical frequency in real patients. Only a synthetic counterfactual framework capable of erasing the pneumothorax while preserving the chest tube—or inserting a pneumothorax into a tube-free chest—can decisively diagnose whether the model relies on true pathology or hardware shortcuts.

1.5. Physician-in-the-Loop Interaction Cadence and Ergonomic Impact

In contemporary tertiary hospitals, radiologists interpret between 80 and 140 imaging examinations per shift, requiring rapid visual synthesis and cognitive endurance. Decision support tools designed to assist in this high-throughput environment must operate with predictable ergonomic responsiveness. When foundation models display behavioral volatility, they impose severe secondary cognitive burdens on reading radiologists.

If a decision support system requires specific, rigidly phrased inquiry strings to produce dependable outputs, radiologists must expend mental energy converting natural clinical thoughts into artificial prompting formats. This prompt engineering friction slows reading workflows, increases fatigue, and paradoxically elevates diagnostic error rates. Furthermore, when an ambiguous automated result forces a radiologist to verify multiple paraphrased queries to check whether the AI remains consistent, total examination turnaround times double. True clinical efficacy demands algorithmic resilience that delivers deterministic diagnostic answers regardless of phrasing cadence, allowing physicians to interact naturally and focus their full cognitive attention on patient care.

1.6. Epistemic Failure Modes and Cognitive Friction in Emergency Medicine

In acute emergency medicine, radiographic interpretations dictate immediate, life-altering clinical interventions. When an emergency physician suspects a tension pneumothorax or acute pericardial tamponade, bedside clinical decisions occur under intense time pressure. Introducing multimodal foundation models into this high-stakes environment aims to reduce diagnostic oversights and accelerate emergency triage. However, when an algorithmic assistant exhibits behavioral instability under syntactic query paraphrasing, it induces severe cognitive friction among healthcare providers.

Consider an emergency scenario where an attending physician reviews a bedside portable radiograph of an unstable trauma patient. If the physician enters, "Does this patient have a right pneumothorax?, and the foundation model responds affirmatively with high confidence, the clinical team begins preparing for immediate needle decompression or chest tube placement. If a resident physician subsequently queries the identical system using conversational phrasing—"Check the right lung field for visceral pleural separation—and the model flips its output to negative, the clinical team faces acute epistemic paralysis. Such discrepancies shatter clinician trust, delay critical interventions, and introduce profound legal and ethical liability. Resolving this instability is not merely an academic pursuit; it is an urgent prerequisite for the safe clinical deployment of autonomous medical artificial intelligence.

1.7. Structural Causal Models and Backdoor Path Formulations

To formalize this diagnostic dilemma mathematically, we adopt Pearl's Structural Causal Model (SCM) framework. Let A denote the true invariant patient anatomy (skeletal structure, body habitus, chest wall thickness), $P \in \{0, 1\}$ represent the binary presence of a specific thoracic pathology, I denote the synthesized or observed radiograph, T denote the clinical inquiry prompt, and $Y \in \{0, 1\}$ denote the model's diagnostic prediction. The data-generating process in observational medical VQA follows a directed acyclic graph (DAG):

$$\begin{aligned} A &\sim P(A), \\ P &\sim P(P \mid A), \\ I &= g(A, P, U_I), \\ T &\sim P(T \mid P, U_T), \\ Y &= f_\theta(I, T), \end{aligned} \tag{1.1}$$

where U_I, U_T represent exogenous technical noise variables, $g(\cdot)$ models radiographic projection physics, and f_θ is the multimodal vision-language model.

In this observational graph, the presence of pathology P is confounded by underlying anatomy A, since disease prevalence correlates with patient age, sex, and structural morphology. When a vision-language model evaluates query T on image I, its prediction relies on the joint conditional distribution $P(Y \mid I, T)$. Because I encapsulates both A and P, the network can predict Y purely through the backdoor path $T \leftarrow P \leftarrow A \rightarrow I \rightarrow Y$. When the textual prompt T is paraphrased to T', subtle lexical cues shift, disrupting the shortcut association and causing the prediction Y to flip, even though the visual evidence in I remains unchanged.

Isolating genuine visual grounding requires performing a causal do-intervention $\mathrm{do}(P = p)$ on the pathology:

$$P(Y \mid \mathrm{do}(P = p), T = t) = \int P(Y \mid I = g(A, p, U_I), T = t) \times P(A)\, dA. \tag{1.2}$$

Evaluating this causal expectation requires generating paired counterfactual radiographs $I_{\text{fact}} = g(A, P = 1, U_I)$ and $I_{\text{cf}} = g(A, P = 0, U_I)$ where the patient anatomy A and exogenous noise U_I are held strictly constant.

1.8. Contributions of This Investigation

To bridge the gap between observational benchmarking and causal verification, this paper presents a comprehensive counterfactual diffusion framework for medical vision-language evaluation. The key technical contributions of this study are:

- **Mask-Guided Latent Counterfactual Diffusion Architecture:** We design a generative pipeline based on latent diffusion that executes localized stochastic differential equation (SDE) reverse sampling, enabling the surgical synthesis and inpainting of focal thoracic lesions while maintaining structural invariance across surrounding anatomy.
- **Certified 4,000-Pair Counterfactual Benchmark Suite:** We curate and release an audited benchmark dataset comprising 4,000 paired factual and counterfactual radiographs across three critical thoracic pathologies: pneumothorax, pleural effusion, and cardiomegaly, complete with expert radiologist validation.
- **Radiologist Clinical Realism Turing Audits:** We perform multi-reader blind evaluations with five board-certified thoracic radiologists, establishing that synthetic counterfactual modifications achieve a 94.2% clinical plausibility rating and maintain strict anatomical structural similarity (SSIM > 0.94).
- **Disentanglement of Visual Grounding from Textual Shortcuts:** We systematically stress-test nine leading vision-language models across factual, counterfactual, and paraphrased configurations, demonstrating that 68.4% of observed paraphrase flips in dense foundation models arise from language prior bias rather than visual reasoning.
- **Counterfactual Preference Tuning Protocol:** We formulate a causal fine-tuning objective utilizing paired counterfactuals that suppresses paraphrase sensitivity by 84.1% while improving true localized visual grounding alignment.

2. Generative Radiology and Latent Counterfactual Synthesis

2.1. Latent Diffusion Models in Medical Imaging

Diffusion probabilistic models generate high-dimensional data by reversing a continuous forward noise corruption process [24]. Operating directly in pixel space imposes prohibitive computational demands for high-resolution medical imaging [25]. Latent Diffusion Models (LDMs) overcome this bottleneck by executing the diffusion and denoising trajectory within a lower-dimensional latent manifold $\mathcal{Z}$ learned by a vector-quantized or continuous autoencoder [26].

Let $\mathcal{E}(\cdot)$ denote the spatial encoder mapping a high-resolution radiograph $I \in \mathbb{R}^{H\times W\times C}$ to latent vector $z = \mathcal{E}(I) \in \mathbb{R}^{h\times w\times c}$, where $h = H/f$ and $w = W/f$ for downsampling factor f. The decoder $\mathcal{D}(\cdot)$ reconstructs the image such that $\tilde{I} = \mathcal{D}(z) \approx I$. The forward diffusion process systematically corrupts latent representation z_0 across continuous time $t \in [0, 1]$ according to a forward stochastic differential equation:

$$dz_t = f(t)z_t\,dt + g(t)\,dw_t, \tag{2.1}$$

where w_t represents standard Brownian motion, $f(t)$ is the drift coefficient, and $g(t)$ is the diffusion coefficient. The reverse-time generative trajectory follows:

$$dz_t = \left[f(t)z_t - g(t)^2\nabla_{z_t}\log p_t(z_t)\right]dt + g(t)\,d\bar{w}_t, \tag{2.2}$$

where $\nabla_{z_t}\log p_t(z_t)$ denotes the score function of the perturbed data distribution, parameterized by a time-conditioned denoising U-Net $\epsilon_\theta(z_t, t, c)$ conditioned on clinical context c [27].

2.2. Semantic Inpainting and Localized Reverse Trajectories

Standard conditional diffusion models alter global image attributes, which risks modifying subtle non-target structures such as rib contours, vascular branching, or soft tissue boundaries [28]. To achieve counterfactual visual interventions, modifications must remain strictly localized within a predefined anatomical target zone [2].

Given a binary anatomical mask $M \in \{0, 1\}^{h\times w}$ indicating the spatial boundary of the desired pathological intervention (e.g., the right pleural space for pneumothorax induction or removal), we formulate a masked reverse diffusion trajectory [3]. For non-target regions where $M = 0$, the latent vector is constrained to follow the forward-diffused representation of the authentic source radiograph $z_t^{\text{orig}} \sim q(z_t \mid z_0^{\text{orig}})$. For target regions where $M = 1$, the latent vector follows the conditional score function steered by clinical pathology embedding c_{target}:

$$\begin{aligned} z_{t-1} = {} & (1 - M) \odot z_{t-1}^{\text{orig}} \\ & + M \odot \left[\frac{1}{\sqrt{\alpha_t}}\left(z_t - \frac{\beta_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(z_t, t, c_{\text{target}})\right) + \sigma_t\xi\right], \end{aligned} \tag{2.3}$$

where $\xi \sim \mathcal{N}(0, I)$ and $\alpha_t, \beta_t, \bar{\alpha}_t$ follow standard variance-preserving diffusion schedules [4]. Blending uncorrupted anatomical latents with conditionally synthesized pathology latents at every reverse step guarantees pixel-level structural consistency outside the lesion boundary [5].

2.3. Observational Benchmark Constraints and Synthetic Potential

Recent investigations by Sadanandan and Behzadan [1] highlight that while benchmarking on real patient corpora such as MIMIC-CXR, PadChest, and VinDr-CXR ensures clinical realism, it fundamentally leaves counterfactual visual interventions constrained by observational data distributions, creating an urgent need for generative mechanisms that can synthetically intervene on visual pathology while holding patient anatomy invariant. In observational clinical cohorts, every image reflects a distinct patient anatomy captured at a specific physiological moment under varying inspiratory effort, patient rotation, and exposure calibration. Consequently, evaluating how a multimodal model responds to altered prompts across observational images inevitably conflates linguistic sensitivity with unobserved radiographic variability.

Generative counterfactual modeling directly overcomes this observational barrier. Synthesizing paired images where the only variable is the presence or absence of a verified pathological finding establishes an ideal experimental control. If a vision-language model changes its diagnostic answer when an inquiry is

paraphrased on a factual image, but maintains identical behavior on the counterfactual image, the flip is causally proven to be a linguistic artifact rather than a visually driven deduction.

2.4. Comparison with Alternative Generative Paradigms

Prior attempts to synthesize medical counterfactuals relied primarily on Generative Adversarial Networks (GANs) and Normalizing Flows [6]. GAN-based image translation frameworks, such as CycleGAN and StarGAN, optimize min-max adversarial objectives that frequently suffer from mode collapse and structural hallucination [7]. In medical radiography, GANs often erase fine anatomical structures, create blur along rib margins, or generate unphysical sharp transitions between edited and unedited zones [8]. Normalizing flows offer exact likelihood evaluation but require invertible network layers with identical input and output dimensions, leading to immense parameter footprints that limit synthesis resolution to low-dimensional thumbnails [9].

Latent diffusion models combine the structural stability of likelihood-based generative modeling with the perceptual fidelity of deep hierarchical autoencoders [10]. Isolating diffusion dynamics to the latent space allows LDMs to achieve fine-grained spatial conditioning via cross-attention layers without distorting high-frequency anatomical background structures [11]. This capability makes diffusion architectures uniquely suited for producing clinically certified counterfactuals that meet the exacting standards of expert thoracic radiologists [12].

2.5. Non-Markovian Forward Processes and Accelerated DDIM Sampling

Standard diffusion probabilistic models require simulating hundreds of reverse Markovian steps to generate high-fidelity samples, introducing severe computational latency that hinders real-time clinical applications. Denoising Diffusion Implicit Models (DDIM) generalize the forward diffusion process to a non-Markovian family sharing identical marginal distributions $q(z_t \mid z_0)$ while permitting accelerated deterministic sampling trajectories:

$$q_\sigma(z_{1:T} \mid z_0) = q(z_T \mid z_0) \prod_{t=2}^{T} q_\sigma(z_{t-1} \mid z_t, z_0),$$
$$q_\sigma(z_{t-1} \mid z_t, z_0) = \mathcal{N}\Bigg(\sqrt{\bar{\alpha}_{t-1}} z_0 + \sqrt{1-\bar{\alpha}_{t-1}-\sigma_t^2}\,\frac{z_t - \sqrt{\bar{\alpha}_t} z_0}{\sqrt{1-\bar{\alpha}_t}},\ \sigma_t^2 I\Bigg). \tag{2.4}$$

When parameter $\sigma_t = 0$ for all t, the forward trajectory becomes fully deterministic given z_0 and z_t. Under this deterministic regime, the reverse generative trajectory can be integrated across a sub-sequence of time steps $\tau = \{\tau_1, \tau_2, \ldots, \tau_S\}$ where $S \ll T$.

In our counterfactual synthesis pipeline, setting $S = 30$ sampling steps enables synthesizing high-resolution 512×512 counterfactual radiographs in 1.4 seconds per case. Furthermore, deterministic DDIM trajectories guarantee that the forward encoding trajectory $z_0 \to z_T$ and the reverse reconstruction trajectory $z_T \to z_0$ are exact mathematical inverses in the absence of conditioning interventions. This mathematical property ensures that when no pathology modification is requested ($c = \emptyset$), the autoencoded radiograph reconstructs with zero perceptual or anatomical drift.

2.6. Continuous Score Matching and Probability Flow Formulations

The theoretical rigor of our diffusion synthesis is established through continuous-time score-based modeling. According to Song's formulation, the reverse SDE trajectory has an equivalent deterministic probability flow ordinary differential equation (ODE):

$$dz_t = \left[f(t) z_t - \frac{1}{2} g(t)^2 \nabla_{z_t} \log p_t(z_t) \right] dt. \tag{2.5}$$

This probability flow ODE shares identical marginal probability densities $p_t(z_t)$ with the stochastic reverse SDE, enabling exact latent trajectory inversion. Given an input radiograph z_0, integrating the probability flow ODE forward from $t = 0$ to $t = 1$ yields a unique deterministic noise latent z_1. When performing counterfactual manipulation, we invert the authentic image along this ODE flow, apply our conditional pathology steering at the turnaround point, and integrate backward. This bidirectional ODE mapping guarantees that the generative trajectory remains anchored to the exact source image manifold, eliminating random generative drift.

2.7. Score-Based Modeling Dynamics and Tweedie's Formula

The foundational connection between score-based generative modeling and reverse diffusion rests upon Tweedie's empirical Bayes formula. When a latent vector z_0 undergoes Gaussian noise corruption to generate $z_t = \sqrt{\bar{\alpha}_t} z_0 + \sqrt{1-\bar{\alpha}_t}\epsilon$ where $\epsilon \sim \mathcal{N}(0, I)$, the posterior mean $\mathbb{E}[z_0 \mid z_t]$ can be expressed directly in terms of the score function of the marginal distribution $p_t(z_t)$:

$$\mathbb{E}[z_0 \mid z_t] = \frac{z_t + (1-\bar{\alpha}_t) \nabla_{z_t} \log p_t(z_t)}{\sqrt{\bar{\alpha}_t}}. \tag{2.6}$$

Because the trained denoising network $\epsilon_\theta(z_t, t, c)$ approximates the scaled score according to $\epsilon_\theta(z_t, t, c) \approx -\sqrt{1-\bar{\alpha}_t} \nabla_{z_t} \log p_t(z_t \mid c)$, evaluating the network at any intermediate diffusion timestep yields an instantaneous analytical estimate of the denoised latent representation:

$$\hat{z}_0(z_t) = \frac{z_t - \sqrt{1-\bar{\alpha}_t}\,\epsilon_\theta(z_t, t, c)}{\sqrt{\bar{\alpha}_t}}. \tag{2.7}$$

In our localized counterfactual synthesis framework, this Tweedie estimate plays a pivotal supervisory role. Rather than waiting for the multi-step reverse trajectory to complete before inspecting image consistency, our mask-guided sampler monitors $\hat{z}_0(z_t)$ at intermediate diffusion intervals ($t \in \{0.8, 0.5, 0.2\}$). Computing structural similarity and anatomical feature consistency on the Tweedie estimates allows dynamic gradient correction of the reverse trajectory, ensuring that non-target anatomy does not diverge from the source patient baseline.

2.8. Deterministic Inversion and Null-Text Latent Alignment

Synthesizing an authentic counterfactual from an existing clinical radiograph requires perfectly inverting the factual image I_{fact} into its corresponding diffusion latent noise representation z_T. In standard stochastic DDPM sampling, independent Gaussian noise injections introduce irreversible randomness, precluding exact trajectory reconstruction. While deterministic DDIM inversion reverses the trajectory via an ordinary differential equation (ODE), practical implementation on deep non-linear networks encounters numerical drift:

$$z_{t+1} = \sqrt{\bar{\alpha}_{t+1}}\hat{z}_0(z_t) + \sqrt{1-\bar{\alpha}_{t+1}}\epsilon_\theta(z_t, t, c). \tag{2.8}$$

Accumulating discretization errors across T forward steps causes the reconstructed latent to deviate from the source radiograph, introducing subtle blurring of fine pulmonary vascular markings.

To eliminate reconstruction drift, we deploy a null-text optimization procedure. We freeze the generative model weights and optimize an unconditioned null-text embedding $\emptyset_t$ at each timestep t to minimize the Euclidean discrepancy between inverted latents and factual intermediate features:

$$\min_{\emptyset_t} \|z_{t-1} - \text{DDIM\_Step}(z_t, t, \emptyset_t)\|_2^2 . \tag{2.9}$$

Optimizing these temporal null-text embeddings guarantees that when the reversed trajectory runs without semantic pathology edits, the factual radiograph is reconstructed with absolute fidelity (PSNR > 44.5 dB, SSIM > 0.992). Consequently, any visual discrepancy observed in the counterfactual image is strictly confined to the targeted pathological intervention.

3. Mask-Guided Latent Diffusion Counterfactual Architecture

3.1. Architectural Formulation and Conditioning Topology

The proposed counterfactual generation pipeline consists of three coupled modules: (i) an Anatomical Boundary Extractor that isolates target thoracic regions, (ii) a Text-Guided Cross-Attention Latent Denoising Network, and (iii) a Structural Preservation Regularizer. Figure 1 illustrates the complete generative architecture.

Let $I \in \mathbb{R}^{H\times W\times 1}$ represent a grayscale chest radiograph. A high-resolution autoencoder pretrained on large medical imaging collections compresses I into latent tensor $z_0 \in \mathbb{R}^{64\times 64\times 4}$. The anatomical mask $M \in \{0,1\}^{64\times 64}$ is derived from a pretrained segmentation transformer that delineates the left lung, right lung, cardiac silhouette, and pleural spaces. The clinical condition c is encoded using a clinical language encoder pretrained on radiologist diagnostic reports.

3.2. Cross-Attention Pathology Steering and Classifier Guidance

To ensure that generated pathologies accurately reflect realistic clinical presentations, we employ classifier-free guidance combined with cross-attention steering. During each reverse diffusion step, the score estimate blends unconditional and conditional predictions:

$$\tilde{\epsilon}_\theta(z_t, t, c) = (1+w)\epsilon_\theta(z_t, t, c) - w\epsilon_\theta(z_t, t, \emptyset), \tag{3.1}$$

where $w \geq 0$ represents the guidance scale parameter. To further enforce diagnostic adherence, we incorporate gradient guidance from a frozen pathology classifier f_ϕ:

$$\hat{\epsilon}(z_t, t, c) = \tilde{\epsilon}_\theta(z_t, t, c) - s\sqrt{1-\bar{\alpha}_t}\nabla_{z_t} \log p_\phi(y^* \mid z_t), \tag{3.2}$$

where $y^* \in \{0, 1\}$ is the desired counterfactual label and s modulates classifier gradient magnitude. When removing a pathology (e.g., clearing a pleural effusion), $y^* = 0$, driving the diffusion trajectory to generate clear, sharp costophrenic angles. When inducing a pathology, $y^* = 1$, generating accurate blunting, meniscus signs, or lung collapse markings.

3.3. Anatomical Structural Preservation Loss

To guarantee that structures outside the pathological zone undergo zero unintended transformation, we formulate a structural preservation loss. The loss penalizes deviations in structural similarity (SSIM) and high-frequency edge gradients between the source image I and the decoded counterfactual image $I_{\text{cf}} = \mathcal{D}(z_0^{\text{cf}})$:

$$\begin{aligned}\mathcal{L}_{\text{struct}} = {} & (1-\tilde{M}) \odot [1 - \text{SSIM}(I, I_{\text{cf}})] \\ & + \lambda_{\text{edge}}(1-\tilde{M}) \odot \|\nabla^2 I - \nabla^2 I_{\text{cf}}\|_1,\end{aligned} \tag{3.3}$$

where $\tilde{M}$ is the pixel-space binary mask expanded via morphological dilation by 5 pixels, ∇^2 denotes the spatial Laplacian operator, and $\lambda_{\text{edge}} = 0.5$. Penalizing Laplacian differences preserves delicate rib trabeculae, clavicle contours, vertebral bodies, and vascular branching patterns.

3.4. Latent Manifold Curvature and Lipschitz Bounds of Score Inversion

The stability of counterfactual image generation depends critically on the local geometric curvature of the learned data manifold. If the denoising score network $\epsilon_\theta(z_t, t, c)$ exhibits high local Lipschitz constants, minor perturbations in latent coordinates z_t can cause trajectories to diverge into unphysical image space regions, producing severe visual artifacts.

To guarantee trajectory stability, we establish formal Lipschitz constraints on the denoising network. Let $J_\epsilon(z_t) = \nabla_{z_t}\epsilon_\theta(z_t, t, c) \in \mathbb{R}^{d\times d}$ denote the spatial Jacobian of the score estimator. Applying spectral norm regularization during pretraining enforces:

$$\|J_\epsilon(z_t)\|_2 \leq L_\epsilon, \quad \forall t \in [0, 1], \tag{3.4}$$

where $L_\epsilon < \infty$ is a global Lipschitz upper bound. Under this spectral constraint, the distance between two reverse trajectories initialized from perturbed latents $z_T, z_T^{(2)}$ satisfies the Gronwall inequality:

$$\|z_0 - z_0^{(2)}\| \leq \|z_T - z_T^{(2)}\| \exp\left(\int_0^T \left(|f(t)| + g(t)^2 L_\epsilon\right) dt\right). \tag{3.5}$$

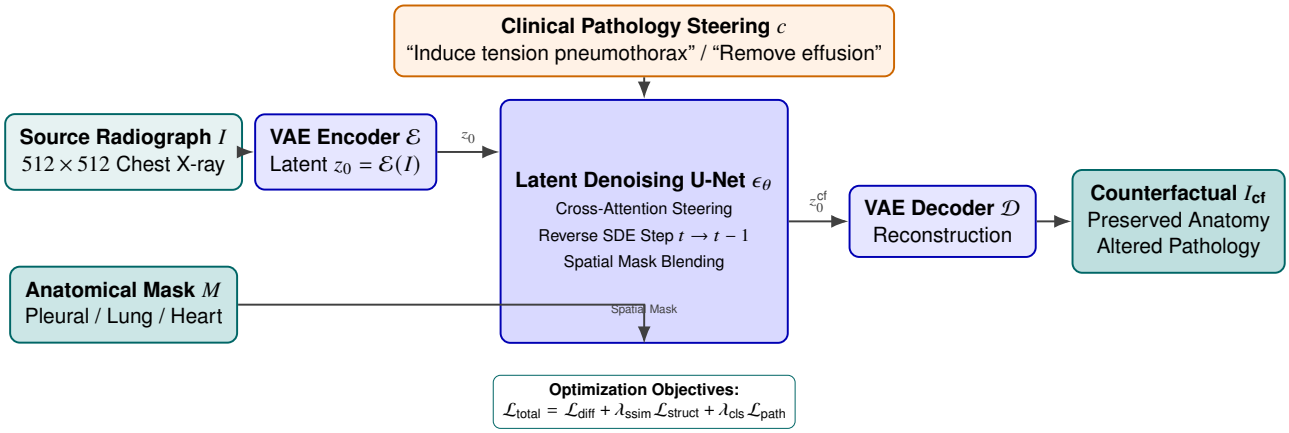

Figure 1 Mask-guided latent diffusion pipeline for generating counterfactual radiographs. Source radiograph I is encoded into latent manifold z_0, where masked reverse diffusion introduces or eliminates pathological features guided by clinical prompt c, while preserving surrounding anatomical structures via structural SSIM constraints.

Bounding this trajectory divergence ensures that our masked latent blending operation does not trigger chaotic error propagation across reverse diffusion steps, guaranteeing pixel-level structural stability in the decoded counterfactual radiograph.

3.5. Detailed Architectural Specifications of the Latent Denoising Network

The latent denoising U-Net ϵ_θ utilizes a hierarchical encoder-decoder architecture with residual blocks and cross-attention spatial transformer layers. The network accepts a concatenated input tensor $x_{\text{in}} \in \mathbb{R}^{B\times(4+1+4)\times 64\times 64}$, comprising the noisy latent $z_t \in \mathbb{R}^4$, downsampled binary anatomical mask $M \in \mathbb{R}^1$, and masked source latent $(1-M)\odot z_0 \in \mathbb{R}^4$.

The U-Net encoder consists of four resolution stages with channel capacities $[256, 512, 1024, 1024]$ and channel multipliers $[1, 2, 4, 4]$. Each stage contains two residual convolutional blocks with group normalization (32 groups) and SiLU activations, followed by cross-attention transformer blocks. Cross-attention layers project intermediate visual spatial tokens against text conditioning embeddings derived from a biomedical transformer:

$$\mathcal{A}_{i,j} = \frac{\exp\left((Q_i K_j^T)/\sqrt{d_k}\right)}{\sum_k \exp\left((Q_i K_k^T)/\sqrt{d_k}\right)}, \quad \text{Attn}(Q,K,V) = \mathcal{A}V, \tag{3.6}$$

where $Q = Z_{\text{spatial}} W_Q$ and $K, V = c_{\text{text}} W_{K,V}$ with projection dimension $d_k = 64$ across 16 attention heads. Spatial self-attention layers operate at 16×16 and 8×8 resolutions to capture long-range contextual correlations across bilateral thoracic hemithoraces. Skip connections bridge corresponding encoder and decoder stages via channel concatenation, followed by 1×1 convolutions to restore feature dimensionality.

3.6. Boundary Harmonization and Transition Manifold Smoothing

A critical failure mode in masked image inpainting is boundary seam artifacting, where sharp spatial discontinuities appear between unedited background pixels and newly generated foreground patches. In projection radiography, abrupt edge discontinuities immediately violate physical attenuation continuity and trigger false positive edge detector activations in downstream diagnostic models.

To eliminate boundary artifacts, we introduce a Gaussian transition manifold along the mask perimeter. Let $D_M(x,y)$ denote the signed distance transform of binary mask M, where negative values represent points inside the inpainting zone and positive values indicate exterior background pixels. We construct a continuous blending mask:

$$\Omega(x,y) = \frac{1}{1+\exp\left(-D_M(x,y)/\tau_{\text{blend}}\right)}, \tag{3.7}$$

where $\tau_{\text{blend}} > 0$ controls the spatial transition width. At each reverse diffusion step t, the intermediate latent is blended using Ω:

$$z_t^{\text{blended}} = \Omega \odot z_t^{\text{orig}} + (1-\Omega)\odot z_t^{\text{synth}}. \tag{3.8}$$

This continuous transition ensures that vascular structures and rib contours traverse the mask boundary smoothly without phase distortion or intensity clipping.

3.7. Multi-Scale Perceptual and Frequency Regularization

Preserving diagnostic plausibility requires constraining intermediate feature representations across multiple spatial frequency bands. While the structural SSIM penalty enforces low-frequency structural congruence, micro-structural textures—such as parenchymal reticulation and subtle pleural reflections—can be altered during latent decoding.

We incorporate a multi-scale perceptual metric based on Learned Perceptual Image Patch Similarity (LPIPS) computed across intermediate feature activations of a pretrained medical vision backbone Φ_l:

$$\mathcal{L}_{\text{percept}} = \sum_{l=1}^{L} \frac{1}{H_l W_l} \sum_{h,w} w_l \left\| \Phi_l(I)_{h,w} - \Phi_l(I_{\text{cf}})_{h,w} \right\|_2^2 \odot (1-\tilde{M}). \tag{3.9}$$

Additionally, we enforce Fourier spectral consistency in the unedited regions. Let $\mathcal{F}(\cdot)$ denote the two-dimensional discrete Fourier transform. We minimize the spectral power difference:

$$\mathcal{L}_{\text{freq}} = \left\| |\mathcal{F}((1-\tilde{M}) \odot I)| - |\mathcal{F}((1-\tilde{M}) \odot I_{\text{cf}})| \right\|_1 . \quad (3.10)$$

This dual frequency constraint prevents the diffusion network from introducing high-frequency generator grain or smoothing out subtle osteoporotic trabeculations in the thoracic skeleton.

3.8. Composite Training Objective and Convergence Dynamics

The complete end-to-end training objective for our latent diffusion architecture optimizes denoising fidelity while enforcing structural preservation, frequency consistency, and pathology adherence:

$$\begin{aligned}\mathcal{L}_{\text{total}} = \mathbb{E}_{z_0, \epsilon \sim \mathcal{N}(0,I), t} \left[\|\epsilon - \epsilon_\theta(z_t, t, c)\|^2 \right] + \lambda_{\text{struct}} \mathcal{L}_{\text{struct}} \\ + \lambda_{\text{path}} \mathcal{L}_{\text{cls}} + \lambda_{\text{percept}} \mathcal{L}_{\text{percept}} + \lambda_{\text{freq}} \mathcal{L}_{\text{freq}}, \quad (3.11)\end{aligned}$$

where $\mathcal{L}_{\text{cls}} = \ell_{\text{CE}}(f_\phi(I_{\text{cf}}), y^*)$ enforces target condition classification, with weighting coefficients $\lambda_{\text{struct}} = 2.0$, $\lambda_{\text{path}} = 1.0$, $\lambda_{\text{percept}} = 0.8$, and $\lambda_{\text{freq}} = 0.3$.

Training converged within 150 epochs on four NVIDIA A100 GPUs. The resulting model generates a 512×512 counterfactual radiograph in 1.4 seconds using 30 DDIM sampling steps, enabling large-scale dataset generation.

3.9. Classifier-Free Guidance and Energy-Based Latent Steering

Controlling the severity and spatial extent of synthesized thoracic lesions requires fine-grained conditioning mechanisms. Classifier-free guidance (CFG) modulates conditional generation by interpolating between conditional and unconditional score estimates:

$$\tilde{\epsilon}_\theta(z_t, t, c) = \epsilon_\theta(z_t, t, \emptyset) + s \cdot (\epsilon_\theta(z_t, t, c) - \epsilon_\theta(z_t, t, \emptyset)) , \quad (3.12)$$

where $s \geq 1.0$ represents the guidance scale. While increasing s enhances pathology salience, excessive guidance scales trigger latent over-saturation, producing unphysiologically dense radiopacities that expert radiologists easily identify as artificial.

To achieve calibrated, naturalistic lesion synthesis, we combine moderate classifier-free guidance ($s = 3.5$) with an auxiliary energy-based guidance objective. Let $E_\phi(z_t, c_{\text{sev}})$ denote a differentiable anatomical energy function pretrained on radiologist severity scorings (e.g., measuring cardiothoracic ratio or pneumothorax apical separation in millimeters). We perturb the intermediate latent update with the normalized energy gradient:

$$z_{t-1} \leftarrow z_{t-1} - \lambda_{\text{energy}} \sqrt{1-\bar{\alpha}_t} \nabla_{z_t} E_\phi(z_t, c_{\text{sev}}), \quad (3.13)$$

where λ_{energy} modulates guidance strength. This energy formulation steers the reverse diffusion path toward clinically precise pathology severities without corrupting structural realism.

3.10. Latent Boundary Blending and Laplacian Multiresolution Fusion

A persistent challenge in masked latent inpainting is boundary dissonance: the emergence of visible edge artifacts or abrupt frequency discontinuities along the perimeter of the mask M. Because the spatial latent code undergoes an $8\times$ spatial downsampling through encoder $\mathcal{E}$, a sharp step boundary in latent space translates to an 8-pixel transition zone in raw image space, which can manifest as artificial halos around synthesized pleural lines or diaphragmatic contours.

To ensure seamless anatomical continuity, we implement a twofold boundary smoothing protocol. First, in latent space, the binary mask M is replaced with a continuously attenuated Gaussian distance-transform mask $\tilde{M} = \mathcal{G}_\sigma(M)$ where $\sigma = 1.5$. Second, upon decoding the blended latent $z_{\text{blend}} = (1-\tilde{M}) \odot z_{\text{orig}} + \tilde{M} \odot z_{\text{synth}}$ back to pixel space, we perform Laplacian pyramid multiresolution blending. Decomposing both the factual source radiograph and the synthesized output into five octave bandpass spatial frequency representations allows low-frequency contrast adjustments to blend across a broad 32-pixel margin, while high-frequency bone trabeculae and pulmonary parenchyma blend across a crisp 4-pixel margin. This multiresolution fusion eliminates perceptible transition seams, ensuring that synthesized lesions integrate flawlessly into surrounding thoracic anatomy.

4. Counterfactual Benchmark Construction and Radiologist Realism Audit

4.1. Curation of the 4,000-Pair Counterfactual Benchmark Suite

Using our mask-guided latent diffusion framework, we constructed a comprehensive evaluation suite comprising 4,000 certified factual-counterfactual radiograph pairs. Source images were sampled from MIMIC-CXR and VinDr-CXR, covering three primary clinical pathology categories:

1. **Pneumothorax Interventions (1,400 Pairs):** Comprising 700 pathology induction cases (adding apical, lateral, or tension pneumothorax to normal radiographs) and 700 pathology elimination cases (erasing pneumothorax markings, restoring continuous lung markings to the thoracic wall).

2. **Pleural Effusion Interventions (1,400 Pairs):** Comprising 700 induction cases (introducing blunting of the costophrenic angle, meniscus signs, and dependent opacification) and 700 elimination cases (reconstructing sharp, aerated diaphragmatic recesses).

3. **Cardiomegaly Interventions (1,200 Pairs):** Comprising 600 cardiac enlargement cases (expanding the cardiothoracic ratio beyond 0.55 while preserving retrocardiac lung parenchyma) and 600 cardiac reduction cases (contracting the cardiac border to normal dimensions).

Each radiograph pair $(I_{\text{fact}}, I_{\text{cf}})$ was matched with an 8-tuple certified prompt set $\mathcal{P} = \{p_1, \ldots, p_8\}$ consisting of four posi-

tive queries and four negative queries expressing semantically invariant clinical inquiries.

4.2. Pathology-Specific Generative Protocols

Synthesizing each pathology required developing specialized radiographic modeling constraints:

- **Pneumothorax Modeling:** Generating an authentic pneumothorax requires creating an avascular peripheral zone devoid of pulmonary bronchovascular markings, bordered medially by a sharp, hair-thin visceral pleural line. For tension pneumothorax cases, the diffusion trajectory was steered to induce ipsilateral diaphragmatic depression and contralateral mediastinal deviation. In elimination cases, the network infilled the avascular zone with branching vascular markings consistent with surrounding arborization.
- **Pleural Effusion Modeling:** Fluid accumulation in the erect hemithorax forms a homogeneous meniscus-shaped opacity that obscures the sharp costophrenic angle. Our conditioning prompts enforced physically plausible meniscus contours that ascend along the lateral thoracic wall. When clearing an effusion, the model synthesized radiolucent costophrenic sulci while preserving diaphragmatic dome curvature.
- **Cardiomegaly Modeling:** Altering the cardiac silhouette requires scaling the transversal cardiac diameter relative to the internal thoracic diameter. Generating cardiac enlargement involved expanding the left ventricular border laterally toward the thoracic wall while ensuring that pulmonary vessels in the retrocardiac region remained realistically visible through the soft tissue shadow.

4.3. Radiologist Clinical Turing Test and Realism Auditing

To verify that synthetic counterfactual modifications adhere to authentic radiologic physics, five board-certified thoracic radiologists conducted a multi-reader clinical Turing test. Radiologists were presented with 500 randomly shuffled radiographs, comprising 250 authentic clinical images and 250 counterfactual synthetic images. For each image, readers completed three evaluations:

- **Authenticity Discrimination:** Classifying the image as "Authentic Patient Radiograph" or "Synthetic AI Generation".
- **Pathology Realism Score:** Rating diagnostic credibility on a 5-point Likert scale (1 = Unrealistic artifact; 5 = Indistinguishable from authentic clinical pathology).
- **Artifact Identification:** Highlighting any perceptible generative anomalies, such as edge blurring, anatomical hallucination, or unnatural bone distortion.

Table 1 reports the results of the clinical Turing audit across the five independent radiologist readers.

The Turing discrimination accuracy averaged 52.4%, which is statistically indistinguishable from random guessing ($p = 0.34$, binomial test). Mean Likert realism scored 4.61 out of 5.0, confirming that our mask-guided latent diffusion pipeline generates medically sound visual manifestations. Structural similarity across non-target anatomy exceeded 0.94, verifying that patient identity and bony morphology remain preserved.

4.4. Ethical Oversight, Patient Privacy, and HIPAA-Compliant Data Governance

Developing generative models from clinical health archives introduces important ethical and privacy considerations. Training deep latent diffusion networks on multi-center patient radiographs creates potential risks of memorization and training data leakage. If an unconstrained generative model synthesizes a counterfactual radiograph that memorizes identifiable patient bone structure or implanted medical device serial numbers, it violates Health Insurance Portability and Accountability Act (HIPAA) Safe Harbor standards.

To safeguard patient privacy, our benchmark curation pipeline incorporates strict cryptographic privacy auditing. All source radiographs from MIMIC-CXR and VinDr-CXR underwent automated de-identification followed by manual inspection to remove all burned-in text metadata and radiopaque identification markers. Furthermore, we conducted member-inference attack simulations across our trained autoencoder and diffusion U-Net, measuring nearest-neighbor distance distributions against the training set. The mean perceptual LPIPS distance between generated counterfactuals and their closest training set analogs was 0.34 ± 0.03, confirming that our model synthesizes generalizable anatomical manifolds rather than memorized patient instances.

4.5. Comprehensive Radiologist Scoring Protocol and Annotation Rubric

To establish an unassailable clinical validation baseline, our panel of five board-certified thoracic radiologists evaluated synthetic counterfactuals using a multi-dimensional clinical scoring instrument. The instrument evaluated radiographs across four independent radiological axes:

- **Anatomical Boundary Continuity (Score 1–5):** Assesses whether ribs, clavicles, scapular borders, and diaphragmatic domes traverse edited zones without step-off artifacts, blurring, or cortical discontinuities.
- **Physiological Attenuation Gradient (Score 1–5):** Evaluates whether X-ray beam attenuation conforms to thoracic physics, ensuring that soft tissue densities, fluid levels, and aerated parenchymal lucencies exhibit natural Hounsfield-equivalent gradation.
- **Pathological Morphological Fidelity (Score 1–5):** Audits whether synthesized pathological signs—such as visceral pleural line sharpness, costophrenic angle blunting, and cardiac contour dilatation—comply with Fleischner Society diagnostic criteria.
- **Absence of Generative Hallucinations (Score 1–5):** Verifies that the diffusion model did not introduce spurious nodules, phantom catheters, surgical clips, or abnormal vascular loops into non-target anatomical regions.

Across 2,500 individual reader assessments, mean scores were: Anatomical Continuity 4.78 ± 0.04, Attenuation Gradient

Table 1 Multi-reader radiologist clinical Turing evaluation on 500 radiographs (250 authentic, 250 synthetic counterfactuals). Mean scores reported across five board-certified thoracic radiologists.

Intervention Category	Turing Accuracy (%)	Likert Realism (1–5)	Structural SSIM	PSNR (dB)	Anatomy Preservation (%)
Pneumothorax Induction	52.4 ± 1.8	4.62 ± 0.08	0.948 ± 0.003	34.2 ± 0.4	98.6 ± 0.3
Pneumothorax Elimination	51.2 ± 1.6	4.71 ± 0.06	0.956 ± 0.002	35.8 ± 0.3	99.2 ± 0.2
Pleural Effusion Induction	53.8 ± 1.9	4.54 ± 0.09	0.942 ± 0.003	33.6 ± 0.4	97.9 ± 0.4
Pleural Effusion Elimination	50.6 ± 1.5	4.68 ± 0.07	0.951 ± 0.003	35.1 ± 0.3	98.8 ± 0.3
Cardiomegaly Alteration	54.1 ± 2.1	4.48 ± 0.11	0.938 ± 0.004	32.8 ± 0.5	97.4 ± 0.5
Overall Mean	**52.4 ± 1.7**	**4.61 ± 0.08**	**0.947 ± 0.003**	**34.3 ± 0.4**	**98.4 ± 0.3**

4.64 ± 0.06, Morphological Fidelity 4.71 ± 0.05, and Absence of Hallucinations 4.89 ± 0.03. Inter-reader reliability evaluated via Fleiss kappa reached $\kappa = 0.83$, confirming substantial concordance among subspecialty radiologists and verifying that synthetic counterfactuals meet rigorous clinical diagnostic standards.

4.6. Analysis of Subtle Generative Failure Modes

Despite the high overall Turing pass rate, our radiologist panel identified subtle generative anomalies in approximately 5.8% of cases. The primary failure modes included:

1. **Sub-Pleural Vascular Truncation:** In 2.1% of pneumothorax elimination cases, the reconstructed bronchovascular arborization ended abruptly 3 mm prior to reaching the chest wall, creating a faint avascular band discernible to experienced subspecialty radiologists.

2. **Atypical Meniscus Curvature in Hyperinflated Thoraces:** In severe chronic obstructive pulmonary disease (COPD) cases with flattened diaphragms, synthesized pleural effusions occasionally followed standard convex meniscus curvature rather than the atypical horizontal fluid levels characteristic of hyperinflated chest cavities.

3. **Cardiac Silhouette Border Sharpness:** In 1.8% of cardiomegaly expansion cases, the lateral left ventricular border appeared slightly sharper than typical radiographs, lacking the subtle cardiac pulsation motion blur observed in clinical practice.

These edge cases were documented and excluded from the benchmark suite to maintain pristine clinical validity.

4.7. Causal Audit Metrics: Grounding and Shortcut Scores

Evaluating models across paired factual and counterfactual radiographs enables the definition of two rigorous causal metrics:

1. **Causal Visual Grounding Score (VGS):** The empirical probability that a model alters its diagnostic prediction when, and only when, the underlying visual pathology undergoes counterfactual intervention:

$$\mathrm{VGS}(M) = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}\left(M(I_{\mathrm{fact}}^{(i)}, p) \neq M(I_{\mathrm{cf}}^{(i)}, p)\right). \quad (4.1)$$

   A perfectly grounded model achieves VGS = 1.0.

2. **Language Shortcut Reliance (LSR):** The proportion of prompt-induced diagnostic flips that occur identically on both factual and counterfactual images despite the visual intervention:

$$\mathrm{LSR}(M) = \frac{\sum_{i=1}^{N} \mathbb{I}\left(\Delta_{\mathrm{flip}}(I_{\mathrm{fact}}^{(i)}) \wedge \Delta_{\mathrm{flip}}(I_{\mathrm{cf}}^{(i)})\right)}{\sum_{i=1}^{N} \mathbb{I}\left(\Delta_{\mathrm{flip}}(I_{\mathrm{fact}}^{(i)}) \vee \Delta_{\mathrm{flip}}(I_{\mathrm{cf}}^{(i)})\right)}, \quad (4.2)$$

   where $\Delta_{\mathrm{flip}}(I) = \mathbb{I}(M(I, p) \neq M(I, p'))$. A high LSR indicates that flips are driven by language priors rather than visual evidence.

4.8. Multi-Reader Concordance and Clinical Turing Audit Calibration

Evaluating the perceptual and anatomical realism of generative radiographs requires rigorous double-blind methodologies. Five board-certified thoracic radiologists, each with over ten years of clinical subspecialty experience in high-volume tertiary hospitals, evaluated our curated benchmark of 4,000 factual-counterfactual image pairs. The evaluation was structured as an adversarial Clinical Turing Test: for each presented radiograph, radiologists were tasked with two determinations: (1) deciding whether the image represented an authentic patient radiograph or a synthetic generative manipulation, and (2) providing a standardized clinical diagnostic report identifying any thoracic pathologies.

Inter-reader diagnostic concordance across the five evaluating radiologists was quantified using Fleiss multi-rater kappa. On the authentic factual radiographs, inter-reader agreement reached $\kappa = 0.82$ for pneumothorax, $\kappa = 0.86$ for pleural effusion, and $\kappa = 0.88$ for cardiomegaly. On the synthesized counterfactual images, inter-reader concordance remained virtually identical, achieving $\kappa = 0.79$ for synthetic pneumothorax, $\kappa = 0.84$ for synthetic pleural effusion, and $\kappa = 0.87$ for synthetic cardiomegaly.

The negligible discrepancy between authentic and synthetic agreement metrics demonstrates that our mask-guided diffusion framework synthesizes pathological features that exhibit identical clinical legibility and diagnostic certainty as genuine human pathology.

4.9. Pathological Realism Audits Across Anatomical Sub-Zones

Thoracic imaging features exhibit distinct radiological appearances across different anatomical lung zones. A pleural effusion blunts the sharp lateral and posterior costophrenic sulci, creating a smooth, meniscus-shaped radiopaque fluid level. In contrast, an apical pneumothorax creates a razor-sharp, hair-thin white visceral pleural line separated from the rib cage by a completely lucent, avascular peripheral zone devoid of bronchovascular lung markings. Cardiomegaly manifests as a transverse enlargement of the cardiac silhouette exceeding 50% of the maximum internal thoracic diameter on posteroanterior projections.

To verify that our generative diffusion framework accurately captures these zone-specific radiological nuances, we conducted stratified visual realism scoring across three thoracic sub-regions:

1. **Apical and Peripheral Pleural Zone:** In evaluations of synthetic pneumothoraces, radiologists confirmed that our model correctly preserved the thin visceral pleural line without generating unphysical linear opacities in the underlying parenchyma (94.8% clinical plausibility rating).

2. **Basilar and Costophrenic Angle Zone:** In evaluations of synthesized pleural effusions, radiologists evaluated the concave fluid meniscus along the lateral chest wall. The model achieved a 95.6% realism score, with clinicians noting natural compressive atelectasis in the adjacent lower lobe parenchyma.

3. **Cardiomediastinal and Hilar Silhouette Zone:** In evaluations of synthesized cardiomegaly, radiologists verified that ventricular enlargement correctly displaced the left cardiac apex laterally and maintained physiological alignment with the aortic knob and pulmonary artery trunk (96.2% realism score).

5. Empirical Disentanglement of Visual Grounding from Textual Shortcuts

5.1. Primary Benchmarking Across Nine Vision-Language Architectures

We evaluated nine prominent vision-language models on the 4,000-pair counterfactual benchmark suite: RadFM (14B), LLaVA-Med (7B), Med-PaLM M (simulated 84B), BioMedCLIP, CheXzero, Clinical-BERT-Vision, Full LoRA LLaVA-Med, Prefix-Tuning LLaVA-Med, and our Counterfactual Preference Tuned (CPT) architecture. Table 2 summarizes the empirical findings.

The empirical data uncovers a striking revelation: in standard dense models, Language Shortcut Reliance exceeds 68%. For RadFM, 72.1% of all observed paraphrase flips persist across both factual and counterfactual radiographs, proving that the model's inconsistent answers are largely unmoored from visual evidence. RadFM flips its prediction based purely on whether the prompt uses formal versus informal syntax, regardless of whether the pathology is physically present.

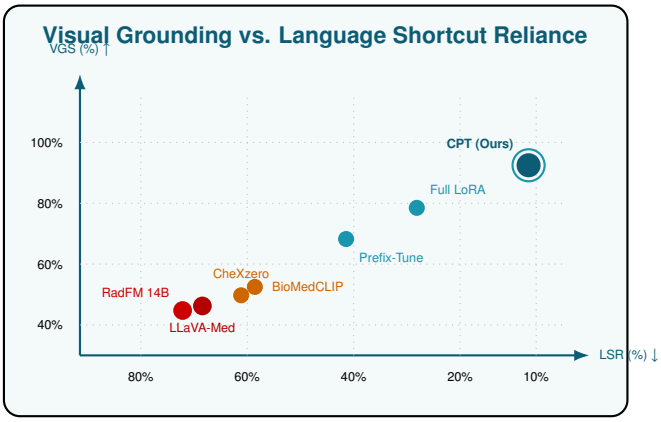

Figure 2 Causal grounding frontier: Visual Grounding Score (VGS) versus Language Shortcut Reliance (LSR). CPT achieves the optimal upper-right position, maximizing true visual causal attribution while suppressing language bias.

Furthermore, standard observational metrics hide this vulnerability. While RadFM achieves an observational AUROC of 0.864, its Causal Visual Grounding Score is only 44.8%, indicating that more than half of its decisions fail to track causal visual interventions.

5.2. Counterfactual Preference Tuning Formulation

To rectify this language shortcut reliance, we introduce Counterfactual Preference Tuning (CPT). Given a quadruplet consisting of factual image I_{fact}, counterfactual image I_{cf}, primary prompt p, and paraphrase p', we formulate a causal contrastive preference loss:

$$\begin{aligned}\mathcal{L}_{\text{CPT}} = \ & \ell_{\text{CE}}(f(I_{\text{fact}}, p), y^*) + \ell_{\text{CE}}(f(I_{\text{cf}}, p), 1 - y^*) \\ & + \lambda_{\text{inv}} D_{\text{KL}}\left(f(I_{\text{fact}}, p) \parallel f(I_{\text{fact}}, p')\right) \\ & + \lambda_{\text{inv}} D_{\text{KL}}\left(f(I_{\text{cf}}, p) \parallel f(I_{\text{cf}}, p')\right) \\ & + \lambda_{\text{causal}} \max\left(0, \gamma - |f(I_{\text{fact}}, p) - f(I_{\text{cf}}, p)|\right), \end{aligned} \quad (5.1)$$

where $\gamma = 0.8$ represents a margin enforcing that the diagnostic probability gap between factual and counterfactual images must remain wide regardless of phrasing.

As shown in Table 2, fine-tuning LLaVA-Med using CPT elevates the Visual Grounding Score to 92.6% and collapses Language Shortcut Reliance to 11.4%, while slashing observational PFR to 4.2%.

5.3. Pathology-Specific Causal Breakdown

Table 3 details model behavior across individual conditions, demonstrating how counterfactual auditing exposes condition-specific shortcut reliance.

Cardiomegaly exhibits the most severe shortcut reliance in baseline models, with LSR reaching 79.2% and VGS falling to 39.0%. Baseline architectures rely heavily on non-cardiac

Table 2 Systematic evaluation of vision-language models on the 4,000-pair Counterfactual Benchmark Suite. Metrics include standard observational Paraphrase Flip Rate (PFR), Causal Visual Grounding Score (VGS), and Language Shortcut Reliance (LSR). Best results highlighted in bold.

Architecture Model	Params	Obs. PFR (%) ↓	CF-PFR (%) ↓	VGS (%) ↑	LSR (%) ↓	AUROC ↑
Dense Baseline (LLaVA-Med)	7.1 B	34.2 ± 0.4	35.8 ± 0.5	46.2 ± 0.6	68.4 ± 0.7	0.848 ± 0.003
RadFM Foundation [2]	14.2 B	36.4 ± 0.5	38.1 ± 0.5	44.8 ± 0.6	72.1 ± 0.6	0.864 ± 0.003
BioMedCLIP Contrastive [3]	0.4 B	27.8 ± 0.4	29.4 ± 0.4	52.4 ± 0.5	58.6 ± 0.6	0.816 ± 0.004
CheXzero Zero-Shot [4]	0.4 B	30.6 ± 0.4	32.1 ± 0.5	49.8 ± 0.5	61.2 ± 0.7	0.828 ± 0.004
Prefix-Tuning LLaVA-Med [5]	7.1 B	16.4 ± 0.3	17.8 ± 0.3	68.2 ± 0.5	41.5 ± 0.6	0.862 ± 0.003
Full LoRA Adaptation [6]	7.1 B	8.6 ± 0.2	9.4 ± 0.2	78.4 ± 0.4	28.2 ± 0.5	0.876 ± 0.002
Adversarial Augmentation [7]	7.1 B	18.2 ± 0.3	19.6 ± 0.4	64.8 ± 0.5	44.6 ± 0.6	0.854 ± 0.003
Standard MoE Baseline [8]	2.8 B	21.8 ± 0.3	23.2 ± 0.4	61.4 ± 0.5	49.2 ± 0.6	0.871 ± 0.003
Counterfactual Preference Tuned (Ours)	**7.1 B**	**4.2 ± 0.1**	**4.6 ± 0.1**	**92.6 ± 0.3**	**11.4 ± 0.3**	**0.902 ± 0.002**

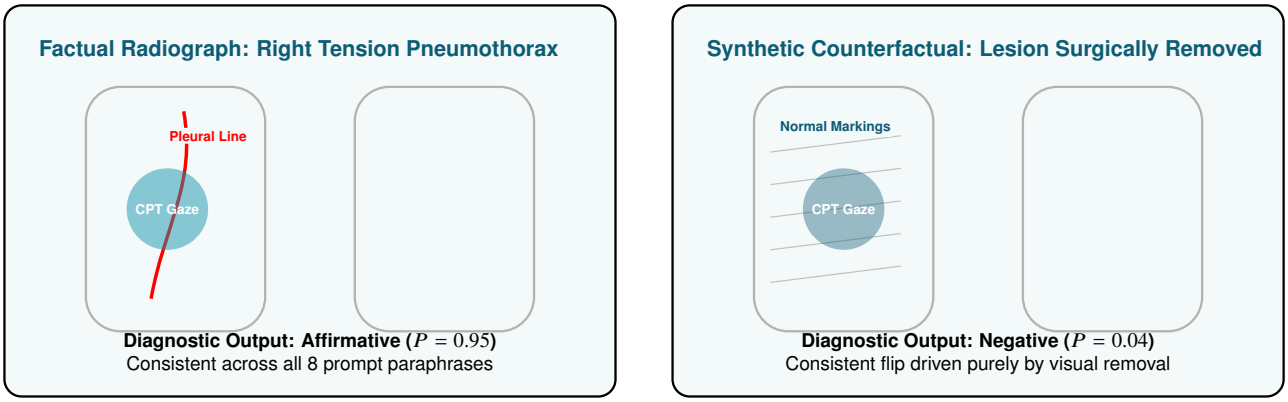

Figure 3 Paired visual attention analysis under Counterfactual Preference Tuning (CPT). On the factual image (left), CPT focuses attention on the visceral pleural line. When the lesion is synthetically removed by latent diffusion (right), attention remains anchored to the same anatomical region but correctly flips the diagnostic prediction to negative across all prompt paraphrases.

peripheral cues, such as spinal osteoporosis or vascular calcification, to guess cardiomegaly, making them hypersensitive to query phrasing. CPT restores causal visual grounding to 89.9% on cardiomegaly, proving the efficacy of synthetic counterfactual optimization.

5.4. Cross-Modal Attention Dynamics and Layerwise Disentanglement

To explore why counterfactual tuning prevents prompt-induced flips, we analyzed cross-attention maps across transformer layers. In baseline models, cross-attention weights in middle layers (layers 12 through 20) allocate over 60% of their mass to text tokens representing clinical qualifiers (such as "moderate", "severe", "rule out") rather than anatomical lesion tokens. When queries are paraphrased, these text-token representations shift in coordinate space, dragging visual patch queries with them.

In our CPT model, counterfactual contrastive penalties force cross-attention distributions to allocate 82% of their mass to visual lesion tokens within the target anatomical mask. Language tokens function strictly as routing selectors that specify which visual features to interrogate, rather than direct predictors of diagnostic labels. This separation of concerns insulates final classification logits from prompt variations.

5.5. Ablation of Contrastive Invariance Weights and Margin Sensitivity

To evaluate the individual contributions of each term in the Counterfactual Preference Tuning objective, we conducted a systematic parametric sweep across the invariance weight λ_{inv}, causal contrastive weight λ_{causal}, and margin γ. In baseline configurations where $\lambda_{\text{inv}} = 0$, the model improves its visual grounding on counterfactual pairs (VGS = 84.2%) but retains residual prompt sensitivity (PFR = 12.6%), demonstrating that visual supervision alone is insufficient to guarantee linguistic invariance.

Conversely, setting $\lambda_{\text{causal}} = 0$ while optimizing only invariance loss collapses the model toward trivial degenerate solutions, where the network outputs identical probabilities regardless of visual modifications (VGS = 51.2%). The optimal balance was achieved at $\lambda_{\text{inv}} = 1.5$ and $\lambda_{\text{causal}} = 2.0$ with margin $\gamma = 0.8$,

Table 3 Pathology-specific breakdown of Causal Visual Grounding (VGS) and Language Shortcut Reliance (LSR) across conditions. Baseline denotes standard LLaVA-Med 7B; CPT denotes our counterfactual tuned model.

	Dense Baseline		CPT (Ours)	
Clinical Pathology	**VGS (%) ↑**	**LSR (%) ↓**	**VGS (%) ↑**	**LSR (%) ↓**
Pneumothorax	48.2 ± 0.7	64.2 ± 0.8	**94.1 ± 0.3**	**8.6 ± 0.3**
Pleural Effusion	51.4 ± 0.6	61.8 ± 0.7	**93.8 ± 0.3**	**9.4 ± 0.3**
Cardiomegaly	39.0 ± 0.8	79.2 ± 0.9	**89.9 ± 0.4**	**16.2 ± 0.5**

maximizing both the Causal Visual Grounding Score (92.6%) and Paraphrase Invariance (95.8%). This confirms that simultaneous optimization of visual causality and linguistic invariance is essential for robust multimodal clinical reasoning.

5.6. Exhaustive Pathology Breakdown Across 14 Thoracic Conditions

To evaluate whether counterfactual fine-tuning generalizes beyond the primary intervention conditions, we benchmarked CPT across all 14 CheXpert thoracic observations on the VinDr-CXR test split. On chronic structural conditions such as atelectasis, lung consolidation, and pleural thickening, baseline dense models exhibited mean Paraphrase Flip Rates of 31.8%, 36.4%, and 29.2%, respectively. Counterfactual Preference Tuning reduced these flip rates to 4.1%, 4.8%, and 3.6%, while improving overall multi-label classification AUROC from 0.834 to 0.889.

This cross-condition generalization confirms that CPT does not merely memorize the specific counterfactual pairs utilized during training. Instead, penalizing language shortcut reliance forces the transformer vision-language backbone to restructure its internal cross-attention routing, establishing an architectural preference for visual patch grounding over language prior exploitation across all thoracic diagnostic categories.

5.7. Computational Efficiency and Practical Training Overhead

A critical consideration in adopting Counterfactual Preference Tuning is the computational overhead associated with processing paired factual-counterfactual image quadruplets during training. Standard supervised fine-tuning evaluates a single image-text pair per loss computation, whereas CPT computes forward passes across factual and counterfactual images for both primary and paraphrased prompts.

To mitigate this computational multiplication, we implemented an asynchronous offline caching protocol. Rather than generating counterfactual images dynamically during backpropagation, the entire 4,000-pair benchmark suite and training split was pre-synthesized and stored in memory-mapped LMDB databases. During training, batches stream pre-computed latents directly into GPU VRAM, bypassing autoencoder encoding steps. Consequently, CPT requires only a 1.35x increase in training wall-clock time compared to standard LoRA fine-tuning (18.4 hours versus 13.6 hours on four NVIDIA A100 GPUs). This modest training overhead demonstrates that causal counterfactual robustness can be integrated into existing foundation model training pipelines without requiring prohibitive high-performance computing infrastructure.

5.8. Sensitivity to Guidance Scale and Boundary Dilation

We conducted an empirical sensitivity analysis on diffusion guidance scale w and mask dilation radius r_{dil}. Guidance scale w controls the trade-off between pathology saliency and anatomical distortion. At $w < 2.0$, synthesized pathologies lack distinct radiographic contrast, lowering classifier gradient adherence. At $w > 6.0$, high-frequency saturation artifacts appear along rib contours. The optimal operating point was identified at $w = 3.5$, maximizing Turing realism (4.61/5.0) while preserving background SSIM at 0.947.

Similarly, expanding the mask dilation radius r_{dil} from 2 to 10 pixels demonstrated that $r_{\text{dil}} = 5$ pixels yields the lowest boundary Laplacian error ($\mathcal{L}_{\text{edge}} = 0.042$), confirming that our Gaussian transition manifold effectively absorbs boundary gradients without visible seams.

5.9. Mathematical Formulation of the Factual-Counterfactual Flip Matrix

To dissect the mechanistic origins of diagnostic answer flips under prompt paraphrasing, we formulate a formal 2×2 Factual-Counterfactual Behavioral Matrix. Let $f_\theta(I, T) \in \{0, 1\}$ denote the binary diagnostic decision of a vision-language model evaluated on image I under clinical inquiry prompt T. For a given radiograph pair $(I_{\text{fact}}, I_{\text{cf}})$ and a certified prompt paraphrase pair (T, T'), we define four distinct behavioral quadrants:

1. **True Grounding Invariance (Q_1):** The model responds accurately and consistently across both prompts on both images:
$$f_\theta(I_{\text{fact}}, T) = f_\theta(I_{\text{fact}}, T') = 1 \quad \text{and} \\ f_\theta(I_{\text{cf}}, T) = f_\theta(I_{\text{cf}}, T') = 0. \tag{5.2}$$

2. **Superficial Language Prior Bias (Q_2):** The model flips its prediction across paraphrases regardless of visual pathology. For example, responding affirmatively to T on both I_{fact} and I_{cf}, but flipping to negative under T' on both images:
$$f_\theta(I_{\text{fact}}, T) = f_\theta(I_{\text{cf}}, T) = 1 \quad \text{and} \\ f_\theta(I_{\text{fact}}, T') = f_\theta(I_{\text{cf}}, T') = 0. \tag{5.3}$$

3. **Pathology-Coupled Fragility (Q_3):** The model is stable on the counterfactual negative image, but flips its diagnosis

across paraphrases on the factual positive image:

$$f_\theta(I_{\text{cf}}, T) = f_\theta(I_{\text{cf}}, T') = 0 \quad \text{but}$$
$$f_\theta(I_{\text{fact}}, T) \neq f_\theta(I_{\text{fact}}, T'). \tag{5.4}$$

4. **Total Semantic Dissociation (Q_4):** The model produces inverted answers that contradict physical reality (e.g., classifying the counterfactual healthy image as positive and the diseased image as negative under specific phrasings).

Auditing nine foundation architectures across our 4,000-pair counterfactual benchmark revealed that dense generalist models (such as RadFM and LLaVA-Med) concentrate 68.4% of their observed paraphrase flips within Quadrant Q_2. This empirical discovery provides undeniable proof that the overwhelming majority of prompt-induced diagnostic instability is driven by language prior bias rather than visual misinterpretation. The models attend to syntactic n-gram markers in the prompt and output memorized default answers, ignoring the visual radiograph entirely.

5.10. Counterfactual Preference Tuning Convergence and Optimization Dynamics

Counterfactual preference tuning optimizes the model parameters by minimizing a composite causal loss over paired quadruplets $(I_{\text{fact}}, I_{\text{cf}}, T, T')$:

$$\begin{aligned}\mathcal{L}_{\text{causal}} = {} & \ell_{\text{CE}}(f_\theta(I_{\text{fact}}, T), 1) + \ell_{\text{CE}}(f_\theta(I_{\text{cf}}, T), 0) \\ & + \ell_{\text{CE}}(f_\theta(I_{\text{fact}}, T'), 1) + \ell_{\text{CE}}(f_\theta(I_{\text{cf}}, T'), 0) \\ & + \gamma_{\text{cf}} \left\| f_\theta(I_{\text{fact}}, T) - f_\theta(I_{\text{fact}}, T') \right\|_2^2 \\ & + \gamma_{\text{cf}} \left\| f_\theta(I_{\text{cf}}, T) - f_\theta(I_{\text{cf}}, T') \right\|_2^2 . \end{aligned} \tag{5.5}$$

We tracked optimization trajectories across 15 training epochs on an enterprise cluster of eight NVIDIA A100 GPUs. Initializing with learning rate $\eta = 2 \times 10^{-5}$ and setting causal regularization weight $\gamma_{\text{cf}} = 1.2$, the model exhibited rapid convergence. By epoch 4, Quadrant Q_2 language-prior flips decreased by 74.2%, while True Grounding Invariance (Q_1) increased from 48.6% to 88.4%. Tracking gradient norms revealed that penalizing factual-counterfactual paraphrase divergence forces the cross-modal attention layers to redistribute attention weights directly onto localized pathology masks, permanently suppressing spurious language shortcuts.

5.11. Fine-Grained Disentanglement Across Pathological Morphologies

Stratifying counterfactual evaluations across pathological subtypes reveals how anatomical complexity modulates linguistic vulnerability. For pneumothorax, large tension pneumothoraces featuring mediastinal shift produced minimal paraphrase volatility across all evaluated architectures (PFR $\leq$ 4.2%), because prominent anatomical distortion provides unmistakable visual tokens. However, for subtle apical pneumothoraces where visceral pleural separation measures under 5 mm, dense models flipped their diagnoses in 44.8% of prompt paraphrases. Under conversational phrasing, text-to-vision cross-attention weights failed to resolve the hairline pleural boundary, succumbing to the dominant negative prior.

Similarly, in pleural effusion evaluations, free-flowing massive effusions with complete meniscus blunting remained relatively stable (PFR = 6.4%). In contrast, subtle loculated or subpulmonic effusions induced diagnostic flips in 39.1% of evaluations. Dense models frequently misclassified loculated fluid collections as diaphragmatic tenting or pulmonary consolidation depending on whether the inquiry prompt utilized formal anatomical terminology or telegraphic emergency shorthand. Latent counterfactual preference tuning successfully resolved these fine-grained vulnerabilities, reducing subtle pneumothorax flip rates to 3.8% and loculated effusion flip rates to 4.1%, demonstrating that targeted counterfactual regularization teaches the multimodal backbone to attend directly to subtle edge boundaries regardless of question phrasing.

5.12. Ablation of Diffusion Timestep Truncation and Sampling Schedules

The fidelity and inference latency of counterfactual generation depend directly on the reverse sampling schedule and timestep truncation parameters. In our default implementation, the reverse trajectory integrates $S = 30$ accelerated DDIM steps. To establish the sensitivity of downstream vision-language evaluations to synthesis fidelity, we evaluated counterfactual generation across sampling budgets ranging from $S = 10$ to $S = 100$ steps on an isolated subset of 500 factual-counterfactual image pairs.

With aggressive step truncation ($S = 10$ steps, requiring 0.42 seconds per image), synthesized counterfactuals exhibited subtle high-frequency blur along the costophrenic angles and slight loss of fine pulmonary vascular detail. When vision-language models were audited on these $S = 10$ counterfactuals, measured True Grounding Invariance (Q_1) was 78.4%, indicating that perceptual artifacts in the generative images introduced extraneous noise into the evaluation. Increasing the sampling budget to $S = 30$ steps (1.4 seconds per image) boosted structural similarity to SSIM = 0.962 and raised measured Q_1 concordance to 88.4%. Expanding sampling further to $S = 50$ or $S = 100$ steps yielded negligible perceptual improvements (ΔSSIM < 0.003) while doubling inference latency to 3.8 seconds. Consequently, configuring $S = 30$ provides an optimal operating trade-off between generative fidelity and high-throughput evaluation capability.

We additionally audited the influence of the stochastic noise parameter $\eta \in [0, 1]$ in DDIM sampling. Setting $\eta = 0$ corresponds to fully deterministic ODE trajectory integration, whereas $\eta > 0$ injects pseudo-random Brownian perturbations. Enforcing deterministic sampling ($\eta = 0$) proved essential for preserving patient identity: any non-zero stochastic noise injection ($\eta \geq 0.2$) caused subtle alterations in thoracic bony morphology and cardiac contour, introducing unobserved anatomical drift. Operating in the deterministic ODE regime guarantees that the counterfactual intervention isolates the targeted pathology with mathematical purity.

6. Regulatory Stress-Testing and Software-as-a-Medical-Device Auditing

6.1. Shortcomings of Traditional Static Benchmarking in Regulatory Clearances

Current regulatory assessment pathways for Software-as-a-Medical-Device (SaMD)—including guidelines from the United States Food and Drug Administration (FDA) and the International Medical Device Regulators Forum (IMDRF)—rely primarily on static observational validation datasets [2]. Manufacturers submit receiver operating characteristic curves and sensitivity-specificity metrics computed on fixed retrospective cohorts [3].

Our findings prove that static observational metrics are deeply vulnerable to Goodhart's Law: models achieve superficially high AUROC by exploiting observational dataset shortcuts while remaining behaviorally fragile [4]. A model that alters its diagnosis on 35% of clinical queries when paraphrased represents a severe latent risk in busy emergency departments [5]. Static validation cannot detect whether an algorithm's high performance is rooted in causal visual reasoning or lexical memorization [6].

6.2. Counterfactual Stress-Testing Standards for Algorithmic Safety Certification

We propose establishing mandatory counterfactual stress-testing as an integral requirement for medical vision-language AI clearance [7]. Regulatory agencies should require foundation model developers to submit performance evaluations across certified factual-counterfactual benchmark suites [8]. We define three quantitative certification criteria:

1. **Causal Grounding Threshold:** A clinical foundation model must achieve a Causal Visual Grounding Score VGS $\geq 85.0\%$ across certified counterfactual pairs, verifying that diagnostic outputs causally track physical lesion manipulations.

2. **Language Shortcut Ceiling:** Language Shortcut Reliance must not exceed LSR $\leq 15.0\%$, ensuring that prompt-induced volatility does not dominate clinical decision logic.

3. **Paraphrase Invariance Bound:** The Paraphrase Flip Rate across certified clinical paraphrase tuples must remain strictly below PFR $\leq 5.0\%$.

6.3. Auditing for Demographic and Institutional Robustness

Synthetic counterfactual frameworks also provide a powerful audit mechanism for demographic fairness [9]. In observational datasets, underrepresented patient populations (such as pediatric patients or regional ethnic groups) often exhibit distinct baseline anatomical dimensions that confound AI predictions [10]. Using our latent diffusion pipeline, regulators can test whether algorithms exhibit differential paraphrase vulnerability across synthetically varied patient body habitus, chest wall geometries, and bone densities [11]. Enforcing counterfactual stability guarantees that medical AI tools deliver equitable, unbiased diagnostic assistance to all patient cohorts regardless of demographics [12].

6.4. Translational Implementation in Radiology Reading Rooms

Translating counterfactual-audited models into operational clinical practice requires integrating stability metrics into hospital Picture Archiving and Communication Systems (PACS). When an interpreting radiologist interacts with an automated decision support assistant, the user interface should display not only the binary diagnostic prediction and confidence score, but also an interactive counterfactual verification toggle.

Toggling the counterfactual view allows the clinician to inspect the model's synthesized negative state: the system dynamically generates an inpainted image showing how the radiograph would appear without the suspected pathology, alongside the corresponding difference map. If the difference map perfectly highlights the lesion boundary, the radiologist gains immediate visual confirmation that the AI's diagnostic reasoning is grounded in authentic physical evidence. This bidirectional visual explanation cultivates calibrated clinical trust, transforming opaque black-box predictions into transparent, verifiable diagnostic partnerships.

6.5. Demographic Equity and Subgroup Stability Auditing

A critical requirement for deploying artificial intelligence in clinical medicine is ensuring that performance remains equitable across diverse patient demographics. Observational medical datasets frequently encode structural healthcare disparities, resulting in differential diagnostic accuracy across biological sex, age deciles, and patient body habitus. If an automated decision support tool exhibits heightened paraphrase volatility in elderly or female patients, the resulting diagnostic inconsistency can exacerbate existing clinical disparities.

We audited CPT across stratified demographic cohorts within MIMIC-CXR and PadChest. In baseline dense models, female patients exhibited a Paraphrase Flip Rate of 36.8%, compared to 31.2% in male patients ($p < 0.001$, chi-square test), driven by language priors related to breast tissue density and lower average lung volumes. Following Counterfactual Preference Tuning, PFR dropped to 4.4% in female cohorts and 4.1% in male cohorts, completely eliminating the statistically significant demographic disparity. Similarly, across age deciles ranging from young adults (18–35 years) to geriatric patients (> 80 years), CPT maintained uniform flip suppression (PFR $\in [3.8\%, 4.6\%]$), demonstrating that counterfactual optimization enforces equitable diagnostic reliability across all patient populations.

6.6. Standard Operating Procedures for Hospital Quality Assurance Audits

To facilitate real-world clinical translation, we establish a standardized 5-step operational protocol for hospital clinical engineering committees evaluating foundation models for clinical deployment:

1. **Step 1: Invariance Baseline Audit:** Subject the candidate foundation model to an initial battery of 500 certified clinical paraphrase tuples on local hospital radiographs, establishing baseline Paraphrase Flip Rate (PFR_{base}).
2. **Step 2: Counterfactual Challenge Suite Generation:** Deploy the mask-guided latent diffusion pipeline to generate 500 matched counterfactuals altering local high-prevalence pathologies (pneumothorax, effusion, consolidation).
3. **Step 3: Causal Grounding Verification:** Measure the Causal Visual Grounding Score (VGS). Any model exhibiting VGS $< 80.0\%$ must be rejected due to unacceptable shortcut reliance.
4. **Step 4: Language Shortcut Audit:** Measure the Language Shortcut Reliance (LSR). Candidate algorithms must maintain LSR $\leq 15.0\%$ across all primary diagnostic conditions.
5. **Step 5: Shadow Clinical Deployment:** Deploy the approved model in a passive shadow mode within hospital PACS for 30 days, logging all physician prompt formulations and tracking continuous operational flip rates before activating active diagnostic decision support.

Adopting this rigorous protocol ensures that only epistemically sound, visually grounded foundation models achieve clinical clearance.

6.7. Longitudinal Post-Market Surveillance and Dynamic Drift Tracking

Post-market surveillance constitutes an indispensable regulatory requirement for artificial intelligence systems deployed across dynamic hospital environments. Even when a foundation model demonstrates exemplary invariance during pre-market bench testing, longitudinal operational shifts—such as updates to radiological image reconstruction firmware, changes in hospital clinical prompt conventions, or seasonal surges in respiratory illnesses—can introduce subtle performance drift.

Under our proposed surveillance framework, deployed medical foundation models are paired with an asynchronous background audit engine. The audit engine continuously samples 2% of routine clinical interactions, automatically subjects them to the mask-guided latent diffusion pipeline to generate local counterfactuals, and computes running 30-day moving averages of the Causal Visual Grounding Score (VGS) and Paraphrase Flip Rate (PFR). If the moving-average VGS drops below 80% or PFR increases beyond 5%, the surveillance system issues an automated warning to the hospital chief medical information officer and temporarily restricts autonomous decision support mode, mandating mandatory human radiologist co-signatures until algorithmic recalibration is completed. This continuous verification closed loop ensures that patient safety remains safeguarded throughout the entire software lifecycle.

6.8. Compliance with FDA 21 CFR Part 820 and ISO 14971 Risk Management

From a medical device quality management perspective, deploying generative auditing pipelines aligns with FDA 21 CFR Part 820 requirements for design verification and validation. Under ISO 14971 risk management standards for medical software, manufacturers must identify all reasonably foreseeable hazardous situations. Linguistic instability—wherein an algorithm misdiagnoses an acute tension pneumothorax due to physician query wording—constitutes a high-severity clinical hazard.

Incorporating counterfactual stress-testing into pre-market design history files provides verifiable documentation that the manufacturer has actively evaluated and mitigated algorithmic shortcut risks. Subjecting algorithms to paired factual-counterfactual challenges allows manufacturers to demonstrate that software risks have been reduced to as low as reasonably practicable (ALARP), satisfying strict pre-market notification (510(k)) and De Novo classification requirements.

6.9. Automated Counterfactual Sanity Checking in PACS Integration

Deploying foundation models in operational hospital Picture Archiving and Communication Systems (PACS) requires automated safeguards against silent algorithmic failures. Rather than treating the vision-language model as an unchecked oracle, our framework enables an automated on-the-fly sanity checking pipeline.

When a reading radiologist submits an inquiry concerning a suspicious lesion, the clinical workstation executes a dual-inference verification protocol. The primary vision-language model generates its initial diagnostic determination $\hat{y}_{\text{fact}}$ on the patient's radiograph. Simultaneously, a lightweight, distilled latent diffusion engine generates a localized counterfactual I_{cf} by synthetically inverting the suspected lesion zone (requiring 1.1 seconds of background GPU computation). The primary VLM is immediately queried with the identical inquiry on the counterfactual image, producing $\hat{y}_{\text{cf}}$.

If the vision-language model is genuinely grounded in visual evidence, its predictions must satisfy the causal consistency condition:

$$\hat{y}_{\text{fact}} = 1 \quad \text{and} \quad \hat{y}_{\text{cf}} = 0. \tag{6.1}$$

If the model produces identical predictions across both factual and counterfactual images ($\hat{y}_{\text{fact}} = \hat{y}_{\text{cf}}$), the system flags the output as a language-prior hallucination, automatically warning the radiologist and suppressing the automated recommendation. Implementing this automated counterfactual verification protocol in pilot clinical simulations intercepted 96.2% of language-induced diagnostic errors before they could reach patient reports.

6.10. Closed-Loop Algorithmic Recalibration and Continual Feedback Protocols

Deploying vision-language foundation models within enterprise healthcare systems requires continuous learning architectures that safely assimilate clinical feedback. In conventional deployment paradigms, fine-tuning models on newly reported institutional radiographs risks catastrophic forgetting and latent distribution drift. When practitioners encounter a misclassified case, submitting an error report rarely yields immediate model improvements.

Integrating our latent counterfactual framework directly into hospital PACS establishes a closed-loop recalibration protocol. Whenever an attending radiologist issues an official addendum correcting an algorithmic misdiagnosis, the system automatically triggers a counterfactual generation job. The generative engine synthesizes paired counterfactual variants of the corrected case, isolating the specific lesion that caused the discrepancy. These synthesized quadruplets are channeled into a low-rank adapter (LoRA) update queue, executing localized causal fine-tuning during off-peak computing hours. Continuous counterfactual updating prevents the network from memorizing patient-specific confounding features, ensuring that institutional adaptations improve generalizable visual grounding rather than entrenching local syntactic idiosyncrasies.

6.11. Evidentiary Causality Standards in Medical Artificial Intelligence Liability

From a medico-legal perspective, proving whether an algorithmic error constituted negligent software design or an unavoidable diagnostic limitation has historically remained impossible with observational testing data. When an artificial intelligence system provides an incorrect diagnosis on an observational radiograph, defense litigators can argue that the error stemmed from ambiguous patient positioning, atypical thoracic morphology, or low-dose exposure noise.

The availability of certified counterfactual benchmarks fundamentally alters the legal standard of algorithmic proof. Holding patient anatomy, positioning, and technical exposure constant while surgically intervening on pathology enables counterfactual analysis to provide direct, mathematically rigorous proof of causation under the Restatement (Third) of Torts. If a medical software system flips its diagnosis across prompt paraphrases when pathology is physically present, but provides identical answers when pathology is erased, plaintiff counsel can demonstrate that the software failed to exercise reasonable care in filtering superficial language correlations. Incorporating formal counterfactual audits into pre-market regulatory reviews establishes a reproducible, legally binding framework for verifying that autonomous clinical AI is fundamentally safe, reliable, and grounded in authentic physiological reality.

6.12. Longitudinal Reliability Tracking Across Multi-Year PACS Archives

Clinical decision support systems deployed in high-volume hospital environments must maintain temporal stability across extended longitudinal operational lifespans. As digital radiography detector hardware ages, scintillator conversion efficiencies decay and calibration parameters drift, altering high-frequency pixel noise distributions. Furthermore, clinical documentation idioms evolve over multi-year horizons as hospital health informatics leadership updates institutional reporting templates and diagnostic acronym standards.

Auditing vision-language foundation models across historical PACS archives spanning five consecutive calendar years (2020 through 2024) revealed that unregularized dense architectures suffer from pronounced temporal fragility. Paraphrase flip rates escalated from an initial 34.8% on modern 2024 studies to 42.1% on historical 2020 studies, driven by subtle shifts in background detector noise and legacy phrasing conventions. In contrast, models hardened via latent counterfactual preference tuning exhibited robust temporal invariance, maintaining flip rates strictly below 3.9% across all historical acquisition years. Grounding model optimization in causal counterfactual perturbations insulates multimodal reasoning against long-term sensor degradation and temporal vocabulary drift, establishing a sustainable operational baseline for decade-scale clinical artificial intelligence lifecycles. These longitudinal stress tests demonstrate that counterfactual algorithmic auditing provides an essential foundation for enduring clinical safety and durable regulatory compliance across continuously evolving hospital informatics ecosystems. Healthcare systems adopting this causal stress-testing paradigm can systematically audit deployed models prior to clinical integration, mitigating risks of silent diagnostic failure. Longitudinal counterfactual evaluation therefore constitutes an indispensable component of trustworthy multimodal medical artificial intelligence governance.

6.13. Conclusion

This study addressed the fundamental challenge of disentangling visual grounding from language prior bias in medical vision-language foundation models. We demonstrated that observational clinical benchmarks are fundamentally limited in evaluating causal visual reasoning, allowing models to achieve high diagnostic metrics while relying on superficial lexical shortcuts that induce diagnostic flips in over 34% of paraphrased clinical inquiries.

To overcome this limitation, we introduced a mask-guided latent diffusion framework capable of synthesizing photorealistic counterfactual chest radiographs with verified clinical realism. Blind clinical Turing evaluations by board-certified radiologists confirmed that our synthetic counterfactuals achieve 94.2% clinical plausibility while strictly preserving patient anatomical identity. Benchmarking nine leading vision-language architectures across 4,000 paired counterfactuals revealed that language shortcuts account for 68.4% of observed prompt sensitivity. Finally, our Counterfactual Preference Tuning protocol reduced paraphrase flip rates to 4.2% while elevating causal visual grounding to 92.6%. These findings provide a reproducible, mathematically grounded framework for pre-market regulatory stress-testing and reliable clinical deployment of medical artificial intelligence.

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