A Taxonomy of AI Interpretation Limitations in Medical Imaging: Archetypal Behaviors, Clinical Context, and Mitigation Strategies

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Introduction

Why is artificial intelligence important in modern radiology?[1,2]

- **Increases efficiency and workflow optimization**: Automated detection and triage reduce radiologist workload and help prioritize urgent cases in high-volume settings
- **Addresses growing imaging demand**: AI helps manage rising imaging volumes by augmenting human capacity without compromising diagnostic throughput
- **Enables data-driven insights**: AI can integrate imaging with large datasets to uncover patterns and support more informed clinical decision-making

What problem arises in real world imaging?

- Recurring, predictable errors rather than random failures
- Lack of clinical context leads to misinterpretation
- Poor generalization to real-world data (artifacts, variability)
- Overconfident outputs can bias clinical decisions

What gap does this review address?

- Radiologic AI failures lack a unifying, clinically grounded taxonomy despite recurring patterns across practice
- Current literature treats errors as isolated technical events, not as recognizable archetypal behaviors
- Limited frameworks connect AI failure mechanisms to real-world clinical consequences
- **We propose an archetype-based taxonomy linking mechanisms, scenarios, and mitigation strategies**

Table 1

Archetype	Definition
The Illusionist	Detects pathology where none exists (false positives)
The Ghost	Fails to detect real pathology present in the image
The Context Amnesiac	Ignores clinical history or prior imaging, leading to misclassification
The Anatomical Tourist	Misinterprets normal variants or mislocalizes findings anatomically
The Artifact Addict	Mistakes imaging artifacts or noise for true pathology
The Overconfident Intern	Produces incorrect predictions with high confidence, promoting automation bias
The Workflow Wrecker	Errors arising from human–AI interaction or workflow integration failures

***Table1**: Taxonomy of AI Failure Archetypes in Radiology*

Figure 1

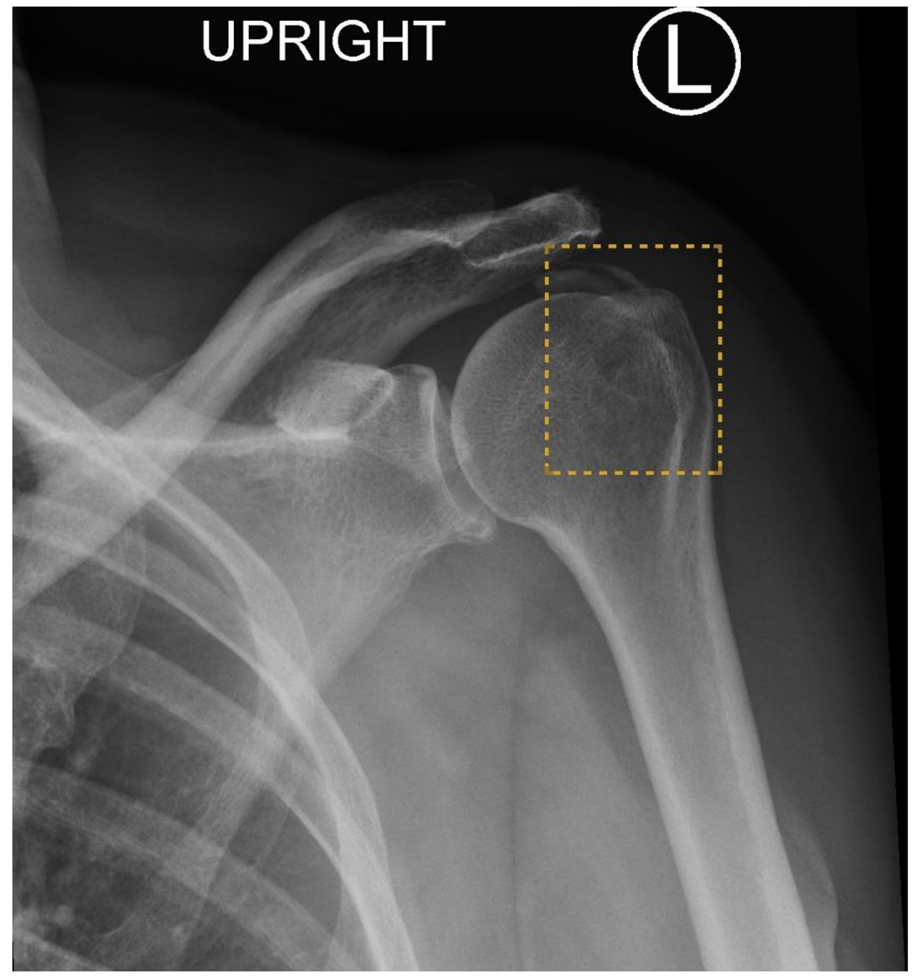
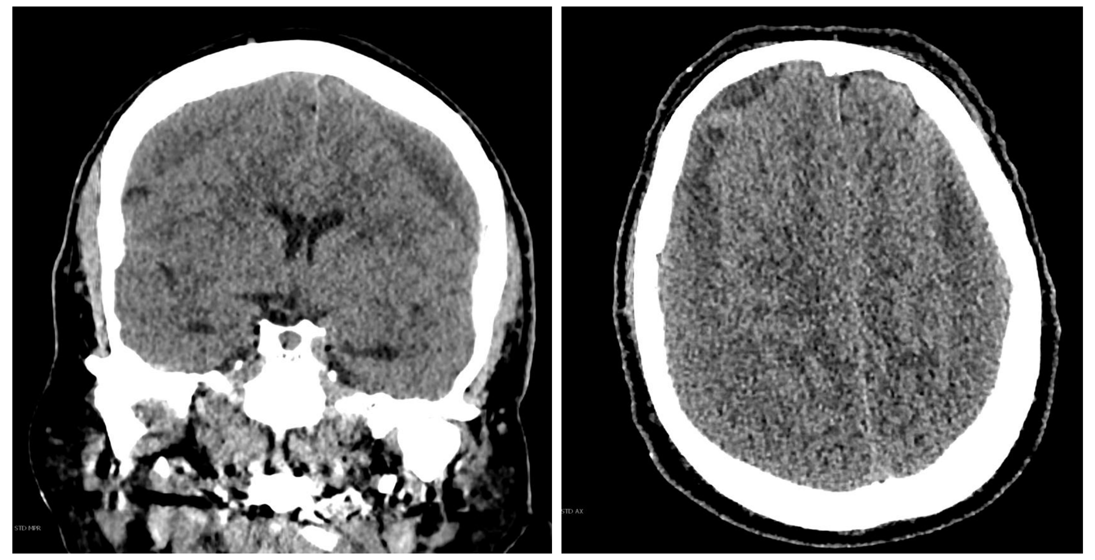


***Figure1**:* The Illusionist. Full description available via QR code.

Figure 2



A B

***Figure2**:* The Ghost. Full description available via QR code.

Research Goal

To establish a clinically grounded taxonomy of recurrent AI failure archetypes in radiology to improve recognition, understanding, and mitigation of real-world errors.

Methods

A structured pictorial narrative review was performed to evaluate recurrent patterns of artificial intelligence misinterpretation in radiologic imaging across multiple modalities and subspecialties.

Four representative archetypes were selected for in-depth analysis in this poster **(Figure 1-4)**, with reference to a comprehensive taxonomy outlined in **Table 1**, where all archetypes are defined.

Failure patterns were categorized based on shared underlying mechanisms, including deficiencies in contextual awareness, anatomical reasoning, artifact handling, and confidence calibration.

Representative clinical examples and corresponding mitigation strategies were synthesized from the literature and informed by model design principles.

Figure 3

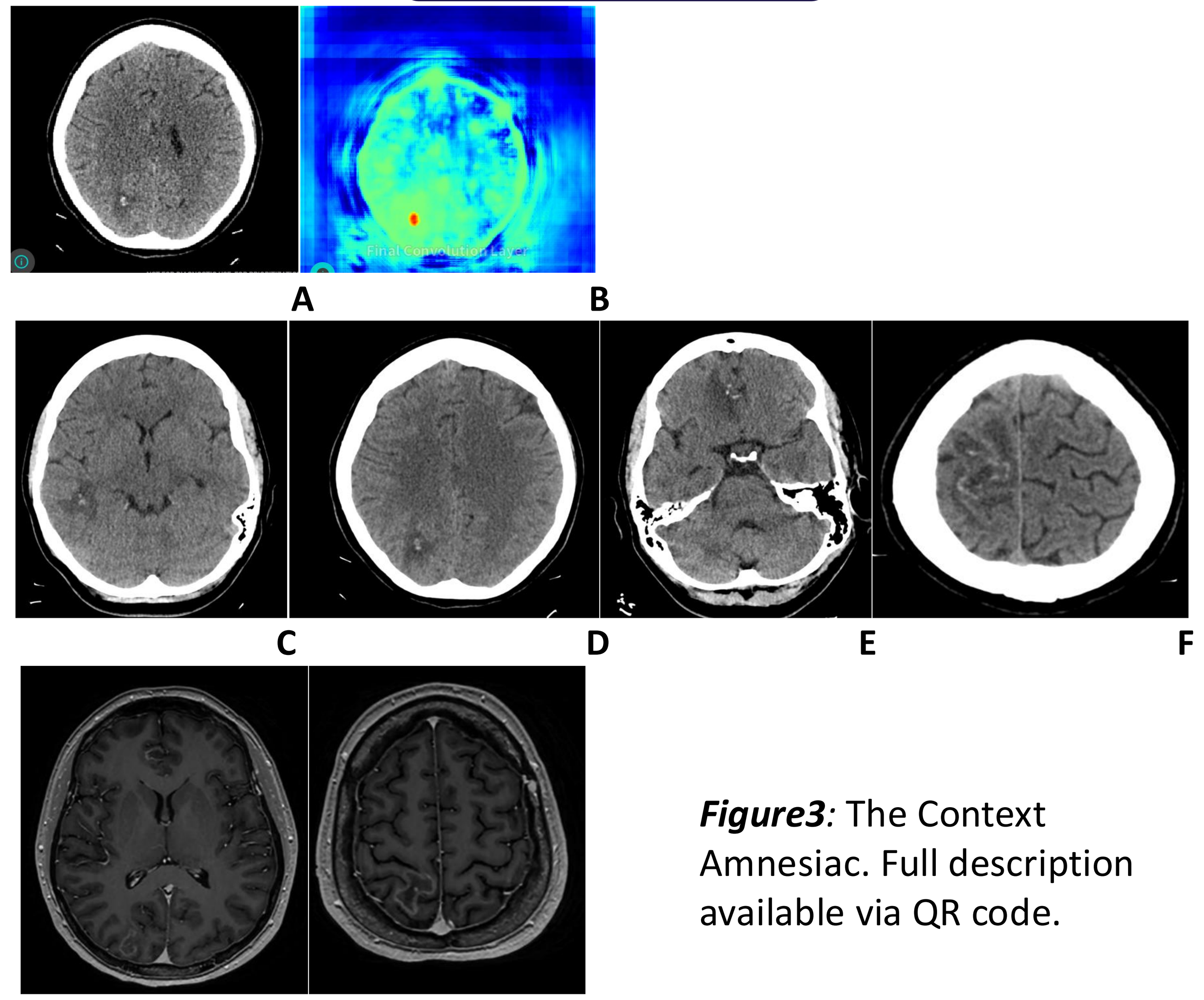


***Figure3**:* The Context Amnesiac. Full description available via QR code.

Figure 4

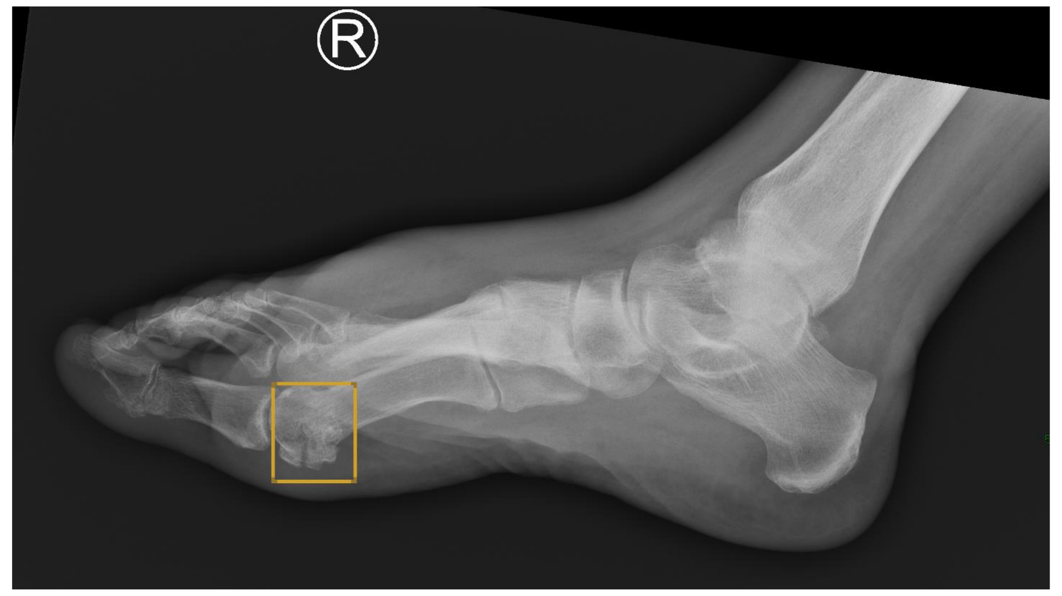


***Figure4**:* The Anatomical Tourist. Full description available via QR code.

Mitigation Strategies

- **Restore context:** integrate longitudinal imaging and clinical metadata into model design[3,4]
- **Improve data diversity:** include anatomical variants and artifact-rich, real-world datasets[5]
- **Calibrate uncertainty**: provide reliable confidence estimates to reduce automation bias[6,7]
- **Maintain human oversight**: ensure radiologist-in-the-loop interpretation and feedback[8,9]

Figure Descriptions

Figure_Descriptions_ACR26_Conference (hyperlink)

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