Teaching Clinical AI Literacy: An Educational Framework for Communicating Risk and Uncertainty in Radiology

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Introduction

AI tools increasingly output precise disease-probability estimates (e.g., “63% likelihood of malignancy”), yet trainees receive little instruction on how to interpret or communicate these values, despite a growing need for explicit teaching on AI communication competencies. Numerical anchoring, calibration variability, and limited training in uncertainty communication may lead learners to overstate precision or misrepresent model limitations. This project aimed to develop an educational framework to teach radiology trainees how to translate AI-derived probabilities into safe, interpretable report language.

Methods

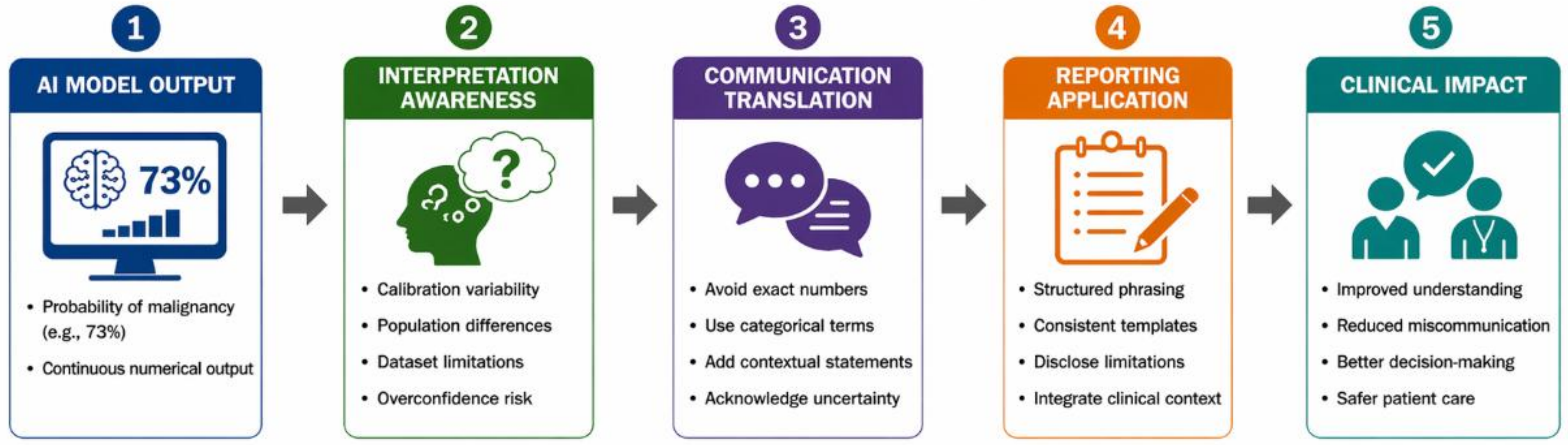
We synthesized concepts from cognitive psychology, medical education theory, radiology reporting instruction, and AI calibration science. These sources informed a structured teaching model that introduces:

1. explanations for why case-level AI probabilities may be unreliable;
2. categorical probability ranges to replace exact numerical outputs;
3. scripts for communicating model limitations, uncertainty, and out-of-distribution situations; and
4. instructional prompts that guide learners on how to integrate AI information with radiologist reasoning rather than treat it as a standalone prediction.

Results

Analysis identified three key trainee learning needs: understanding calibration variability, avoiding over-interpretation of precise numbers, and consistently contextualizing AI predictions within expert assessment. The resulting framework uses categorical language, uncertainty statements, and reporting checklists to support communication skills. This structure reduces cognitive load, promotes conceptual understanding, and encourages consistent learner performance.

Educational Framework for Communicating AI Risk and Uncertainty



Recommended Categorical Language for Risk Communication

Risk Category	Estimated Probability	Example Language	Interpretation Guide
Low Risk	< 20%	“Low risk of malignancy.”	Findings are unlikely to represent malignancy, though not excluded.
Moderate Risk	20–80%	“Moderate risk of malignancy.”	Indeterminate range; integrate with imaging features and clinical context.
High Risk	> 80%	“High risk of malignancy.”	Findings are likely to represent malignancy, though not certain.

Conclusion

AI-generated malignancy probabilities create distinct communication challenges for trainees. A structured educational framework grounded in cognitive psychology and reporting pedagogy can improve learner ability to convey AI-derived risk and uncertainty. Incorporating this model into residency teaching may enhance clarity, reduce miscommunication, and strengthen clinical AI literacy.

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