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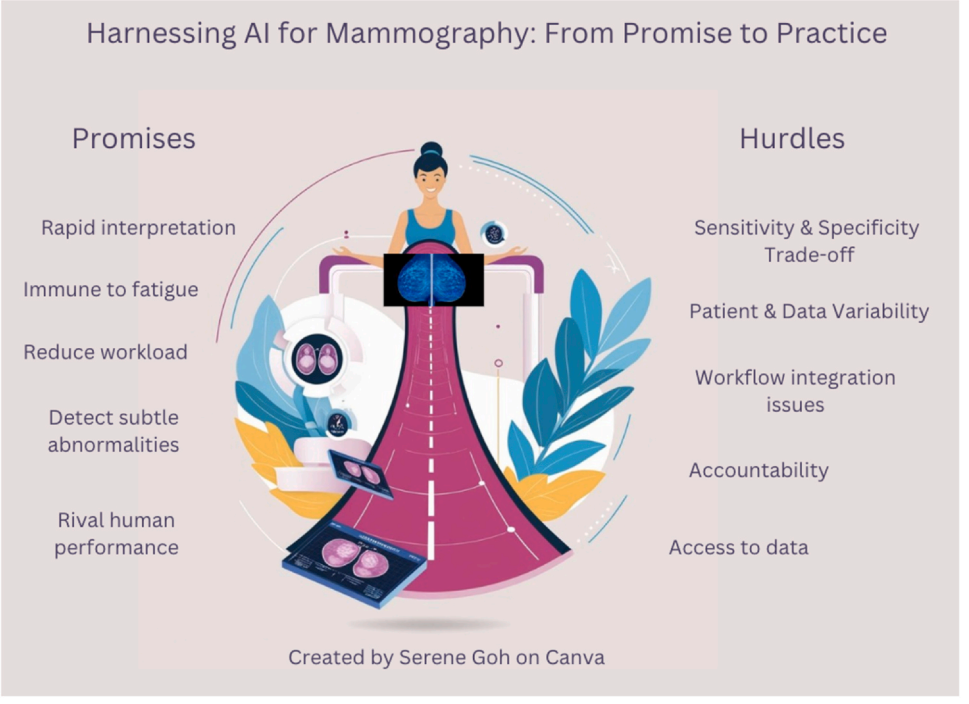
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Commentary

From promise to practice: Harnessing artificial intelligence for breast cancer screening

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Mammographic screening has been pivotal in early breast cancer detection, significantly reducing mortality by enabling timely detection for interventions.[1] Mammography remains the gold standard for breast cancer screening due to its proven ability to detect early-stage cancers and its accessibility for large-scale population screening. Unlike ultrasound, which is typically used as a

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supplementary tool for dense breast tissue, or MRI, which is often reserved for high-risk cases due to its high cost and longer procedure time, mammography provides a standardized, cost-effective modality suitable for widespread use. By applying artificial intelligence (AI) in mammography, healthcare systems can enhance the accuracy and efficiency of screening programs, particularly in high-volume settings. However, interpreting mammograms requires highly trained specialists, and training radiologists is both time consuming and resource-intensive.

Entering offers a transformative opportunity to promote screening by swiftly analyzing images and improving diagnostic accuracy. AI operates swiftly and is immune to fatigue-related errors, allowing higher screening volume without the need for a proportional increase in radiologist staffing. It also can detect subtle patterns, such as microcalcifications or abnormalities in dense breast tissue and has been shown to rival human performance, sometimes even exceeding it in certain contexts.[2] In a Swedish study, using AI alongside one radiologist was comparable to a double reading by two radiologists, highlighting its potential to streamline screening without sacrificing accuracy.[2]

Despite the clear benefits, the integration of AI into breast cancer screening poses significant challenges. Primary among these is balancing sensitivity and specificity.[3] High sensitivity is vital for detecting early-stage cancers, particularly in high-risk groups, yet it can lead to more false positives, causing anxiety and unnecessary follow-ups. However, prioritizing specificity may risk missing early-stage cancers, allowing them to progress to advanced stages, which could cause worse outcomes and erode trust in screening programs. In addition, patient variability adds complexity. Factors such as breast density and demographic differences influence how AI interprets mammograms.[4] Ultimately, the decision to prioritize sensitivity or specificity must align with the unique needs of the target population, available resources, and the goals of the screening initiative. Current AI systems may not perform equally across all populations, making tailored algorithms necessary for optimal accuracy. A dynamic, hybrid strategy where AI calibration adjusts based on patient risk levels and the maturity of the screening program may offer a more balanced approach. The testing of various thresholds and continuous evaluations with feedback loops are essential for fine tuning the system over time, ensuring it remains aligned with clinical outcomes and patient expectations.

Another challenge is integrating AI into radiology workflows.[5] While AI can augment radiologists' work, its introduction requires a re-evaluation of roles, supported by clear communication and comprehensive training. Successful integration surpass simply utilizing technology; it requires radiologists to leverage AI to assist in interpretation, improve diagnostic accuracy, and reduce cognitive biases. Although AI is associated with increased false positive rates, studies show that radiologists using these systems can still maintain their specificity. This points to a potential learning effect, where radiologists adapt their interpretations based on the AI's recommendations.[6] Consequently, this process involves developing a nuanced understanding of when to depend on AI insights, identifying potential limitations or biases within algorithms, and recognizing scenarios in which human expertise should take precedence. To build confidence and competence, case-based learning, simulations, and real-world experiences with AI-enhanced diagnostics are likely important pieces of the integration process. Over time, this iterative approach may allow radiologists to refine their clinical judgment, ensuring that AI serves as a collaborator that complements their skills and enhances decision-making.

Current AI software for mammography is limited in certain cases, such as in post-surgical breasts or post-biopsy breasts.[7] Many AI algorithms are not yet trained to interpret the specific changes in breast tissue following surgery, such as scarring, reconstructive alterations, or the presence of metal clips from prior biopsies or surgeries. Without training to recognize these features, AI systems may mistakenly flag them as suspicious, increasing the risk of false positives. This can lead to unnecessary recalls, additional imaging, biopsies, and added anxiety for patients. Training AI on datasets that include images with post-surgical clips and scarring can help the system distinguish between benign markers and actual signs of malignancy, improving diagnostic accuracy. The skill of integrating clinical and surgical histories into image interpretation is what makes human radiologists still essential in the screening workflow, particularly in more complex cases. Until these capabilities are developed, patients with post-intervention changes may not fully benefit from AI-based mammography.

To effectively adapt to AI-assisted mammography, residency programs can consider incorporating targeted training for radiologists that combines theoretical knowledge of AI with practical skills.[8] The curriculum should include an introduction to AI concepts and machine learning algorithms tailored to mammographic interpretation. Following this foundational knowledge, in-depth sessions should focus on the clinical applications of AI, incorporating case studies that demonstrate successful implementations in breast cancer detection and ameliorated diagnostic accuracy. Practical training should include hands-on workshops at which residents can analyze AI-generated mammograms, fostering critical evaluation skills essential for clinical practice. Additionally, ethical considerations regarding late to data privacy and algorithmic bias should be addressed through engaging case discussions that encourage thoughtful dialogue. Finally, promoting collaboration among residents, data scientists, and AI developers will optimize the integration of AI technologies into clinical practice, ultimately enhancing patient outcomes in breast cancer screening.

Accountability is also a key concern. Who takes responsibility when errors occur? In today's landscape, human-in-the-loop (HITL) systems are likely the most common method for integrating AI into clinical practices. These systems combine human expertise with AI, allowing a collaborative decision-making process that increases diagnostic accuracy and efficiency. Hence, the question of responsibility for errors that arise from AI use in mammographic assessments is complex and multifaceted, necessitating shared accountability among all the stakeholders involved. While radiologists likely maintain primary responsibility for interpreting AI-generated results and making clinical decisions in HITL systems, AI developers must also assure their algorithms are accurate and reliable. Ongoing real-world studies should inform necessary adjustments and improvements to AI systems.[9] It is crucial to foster an environment of learning and progress by allowing radiologists to report errors without fear of punitive repercussions.

Data privacy concerns and limited access to large, high-quality datasets also present barriers. AI systems need vast amounts of data to ensure accuracy across settings. However, stringent data protection laws and complex regulatory frameworks can impede data collecting and sharing. Variability in reporting standards across institutions further exacerbates inconsistencies in integrating these

datasets. Multi-center collaborations can strengthen resource pooling and compliance with local regulations, increasing sample size and diversity. Longitudinal studies tracking patient outcomes over time can illuminate the long-term benefits and cost savings associated with AI-enhanced screening. Implementing standardized reporting practices across institutions can facilitate consistent data collection methods and outcomes. This consistency is an important step for developing reliable AI applications in mammography.

Moreover, understanding how women perceive AI's role is vital for assessing its impact on breast cancer screening, as these perceptions affect the acceptance and trust in such innovations. Women often have diverse opinions about AI, ranging from optimism about its potential to concerns about data privacy and the loss of personal interactions with healthcare providers. Incorporating patient feedback into the integration of AI can provide a more holistic view of its effectiveness and acceptance in clinical practice. A recent mixed-methods study[10] found that many women are uncertain or have ambivalent opinions about the use of AI, indicating a need for further persuasion to build their trust in its applications. By actively engaging women in discussions about their experiences and preferences regarding AI-assisted screening, healthcare providers can better address concerns and tailor AI applications to meet patients' needs. This collaborative approach not only fosters trust and transparency but also improves the overall patient experience, guaranteeing that AI technologies are developed and implemented in a manner that aligns with patients' values and expectations.

While AI certainly holds immense promise for breast cancer screening, its path from promise to practice requires the thoughtful navigation of key challenges. It is essential to balance sensitivity and specificity, account for variability within populations, train AI systems on post-surgical breast data, ensure seamless workflow integration, provide workforce training, establish accountability, address data privacy issues, and align with women's expectations. With careful consideration and innovative solutions, AI can revolutionize breast cancer screening and significantly improve patient outcomes.

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CRediT authorship contribution statement

S.G.S.N.: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **M.H.:** Writing – review & editing, Visualization, Supervision.

Declaration of Competing Interest

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References

1. Fuller MS, Lee CI, Elmore JG. Breast cancer screening: an evidence-based update. *Med Clin North Am.* 2015;99(3):451–468.
2. Dembrower K, Crippa A, Colón E, Eklund M, Strand F. ScreenTrustCAD trial consortium. Artificial intelligence for breast cancer detection in screening mammography in Sweden: a prospective, population-based, paired-reader, non-inferiority study. *Lancet Digit Health.* 2023;5(10):e703–e711.
3. Liu J, Lei J, Ou Y, et al. Mammography diagnosis of breast cancer screening through machine learning: a systematic review and meta-analysis. *Clin Exp Med.* 2023;23(6):2341–2356.
4. Moore JX, Han Y, Appleton C, Colditz G, Toriola AT. Determinants of mammographic breast density by race among a large screening population. *JNCI Cancer Spectr.* 2020;4(2):pkaa010.
5. Kim B, Romeijn S, van Buchem M, Mehrizi MHR, Grootjans W. A holistic approach to implementing Artificial intelligence in radiology. *Insights Imaging.* 2024;15(1):22.
6. Yoon JH, Kim EK. Deep learning-based Artificial intelligence for mammography. *Korean J Radio.* 2021;22(8):1225–1239.
7. Mansour S, Azzam H, El-Assaly H. Artificial intelligence as a negative predictive tool for breast cancer postoperative recurrence. *Egypt J Radio Nucl Med.* 2024;55:102.
8. van Kooten MJ, Tan CO, Hofmeijer EIS, et al. A framework to integrate Artificial intelligence training into radiology residency programs: preparing the future radiologist. *Insights Imaging.* 2024;15:15.
9. Habli I, Lawton T, Porter Z. Artificial intelligence in health care: accountability and safety. *Bull World Health Organ.* 2020;98(4):251–256.
10. Lennox-Chhugani N, Chen Y, Pearson V, Trzcinski B, James J. Women's attitudes to the use of AI image readers: a case study from a national breast screening programme. *BMJ Health Care Inf.* 2021;28(1):e100293.