

Human-in-the-Loop AI in Diagnostic Imaging: Roles of Physician Assistants in Supporting Safe and Efficient Radiology Practice

Muralidharan Radhakrishnan¹, Vijaya Lakshmi Thiagarajan¹, Neethirajan Guruswamy², Loganayaki Somasundaram^{1*}

¹ Tutor, KG Hospital and Post Graduate Medical Institute (Affiliated to The Tamil Nadu Dr. M.G.R. Medical University, Chennai), Coimbatore, Tamil Nadu, India.

¹ Assistant Professor, KG Hospital and Post Graduate Medical Institute (Affiliated to The Tamil Nadu Dr. M.G.R. Medical University, Chennai), Coimbatore, Tamil Nadu, India

² Dean-Research, KG College of Arts and Science, Coimbatore, Tamil Nadu, India.

*Corresponding Author

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ABSTRACT

Artificial intelligence (AI) is increasingly becoming incorporated into diagnostic imaging for image interpretation, triage, reconstruction, quantification, workflow optimization and report generation. The effectiveness of such tools goes beyond the algorithms but also relies on how the AI-derived information is interpreted and translated into actions. Human-in-the-loop systems allow trained medical practitioners to mediate between the AI-derived information and the action taken by the practitioner. This review outlines the potential of Physician Assistants (PAs) to assist in safe and efficient use of artificial intelligence in radiology practice. Evidence has been found to show that the inclusion of AI-assisted interpretations improves selected diagnostic tasks. However, external validation and clinical evidence are key factors to consider. Studies conducted recently have shown degradation in performance on external data, whereas new research on human-AI collaboration has identified automation bias, user interface, integration in the workflow, skill effect and governance as factors contributing to clinical value. PA can add value through provision of clinical context, patient preparation, urgency identification, communication and coordination, discrepancy reporting and quality improvement activities. Safe implementation of AI in radiology involves local validation, training in roles, performance monitoring, escalation process, privacy and multidisciplinary governance. The outputs from AI systems must only be treated as supporting information to make decisions and should never replace qualified radiological analysis.

Keywords: Artificial intelligence; Diagnostic imaging; Radiology; Physician assistant; Human-in-the-loop; Patient safety

INTRODUCTION

AI technology has shifted from a primarily experimental focus to its practical implementation in healthcare where diagnostic imaging represents one of the most active domains of AI clinical application. Radiology is especially favourable for AI since the imaging creates large amounts of digitized data which can be analyzed using machine learning, deep learning and natural language processing approaches. The current AI applications include image reconstruction, anomaly detection, prioritization of the worklist, segmentation, quantitative assessment, screening, structured reporting and clinical documentation.

However, the clinical effectiveness of an imaging AI tool cannot be determined based on its strong performance in the development set alone. According to the RAISE systematic review, the vast majority of

radiology AI studies were performed retrospectively and that among studies with directly comparable external validation, performance degraded on average by 6% (Kelly et al., 2022). Recent research supports the same trend – the systematic review conducted in 2025 showed a median decrease in AUC of approximately 0.03 at external validation and identified greater reduction in specificity in certain situations (Suleman et al., 2025).

Recent literature has also moved away from the algorithm in isolation to the human-AI system in which it is applied. In a 2026 narrative review, Kocak & Cuocolo (2026) noted diagnostic complementarity, workflow integration, automation bias, algorithmic aversion, deskilling, workload and governance issues as key elements in responsible implementation of radiology AI. Another 2026 narrative review highlighted the role of cognitive, interface and organisational/medicolegal biases in human-AI interaction (Kim et al., 2026).

In such an environment, Physician Assistants (PAs) might play an auxiliary role in AI-based imaging pathways. Their scope of duties varies according to jurisdiction and organisation but can include clinical assessment, patient preparation, documentation, communication, and co-ordination of care. The use of point-of-care ultrasound (POCUS) by PAs has been also documented, in a scoping review of 30 studies out of 717, in which PAs were found to utilise a variety of POCUS applications, despite the limitations of training and equipment availability (Zak & Monti, 2022).

The purpose of this narrative review is to present the human-in-the-loop framework for diagnostic imaging and potential PA involvement in safe and clinically responsible AI-assisted radiology.

REVIEW

Application of AI in Diagnostic Imaging

AI image analysis tools can identify patterns indicating presence of abnormalities in radiographs, CT, MRI, mammography, and ultrasound images. The applications include specialized tasks ranging from detection to segmentation, quantification, and workflow prioritization. The latest research suggests the use of AI in clinical tasks is useful, but performance and clinical utility differ across diseases, modalities, datasets, and workflows.

A systematic review and meta-analysis conducted in 2025 involving multi-reader multi-case studies in cancer imaging encompassed 34 studies, 23 of which were involved in the meta-analysis. The pooled sensitivity for clinicians was 0.67, and with AI assistance, it was 0.79, whereas the pooled specificity was 0.82 and 0.87, respectively. However, half of the studies had issues of bias according to QUADAS-C (Zhao et al., 2025).

In 2026, a scoping review of randomized controlled trials on the use of AI in radiological diagnostics found that AI technologies were primarily employed as decision aids for clinicians. In nine RCTs conducted, AI generally helped to enhance sensitivity or lesion detection and to decrease image processing times, though the results were less favourable in complex situations and there was often low specificity (Yan et al., 2026).

Workflow Prioritization and Triage

AI is able to assess imaging work-lists and mark those exams for potential urgent findings like intracranial haemorrhage, pulmonary embolism, pneumothorax, large vessel occlusions or bone fractures. This can help to triage human review of images but should not be considered as diagnostic tool. This differentiation of triage and diagnosis becomes especially important in case of possible false-negative cases that might result in delayed treatment.

Image Reconstruction, Segmentation and Quantification

Deep learning image reconstruction can decrease noise level and make image acquisition or reconstruction more effective. Automated segmentation can detect organs, lesions or other structures and provide quantitative measurements of volume. These tools might assist in tumour evaluation, organ-volume evaluation, lungs, heart evaluation and response to treatment assessment. Human validation is required in case of measurements

that affect diagnosis and/or treatment decisions in case of motion, unusual anatomy, technical artifacts or different acquisitions.

Generative AI in Radiology Report

Generative AI and LLMs are being studied more and more for applications related to radiology report creation, summarization, translation, extraction of structured data and workflow support. One 2026 scoping review of 69 papers indicated the positive results achieved in simplifying reports and translating them but showed a mix of results in classification, many shortcomings in validation, generalizability and management of stochasticity of the model (Lee et al., 2026). A different 2026 review dedicated to human-AI collaboration stressed the impact of the interface, time and presentation of AI results on their usage by the clinician (Kim et al., 2026). Hence, the AI generated text should be checked against source information and the final qualified interpretation before the clinical communication.

METHODOLOGY

This paper is a narrative review accompanied by an update of recent literature relevant to the topic (Grant & Booth, 2009; Baethge et al., 2019). The uploaded draft served as the main conceptual framework for the review and recent literature relevant to diagnostic imaging AI, external validation, human-AI interaction, generative AI in radiology, AI-enhanced diagnostic accuracy, AI-powered POCUS, and trustworthy AI governance was searched for using PubMed and journal or publisher webpages (Snyder, 2019). Systematic reviews, scoping reviews, consensus documents, and recent (2025-2026) articles were prioritized. In view of being a narrative review, no meta-analysis was performed in this paper and quantitative data from individual papers was described but not statistically synthesized.

The review highlights four interlinked themes: (1) use of AI in diagnostic imaging; (2) issues related to generalizability, safety, and human factors; (3) possible PA contribution within its scope of practice; and (4) governance, education, and monitoring needs for safe implementation.

Human-In-The-Loop AI Model

The suggested AI human-in-the-loop approach depicts how AI can be incorporated within diagnostic imaging with proper human oversight. It starts with formulation of the clinical problem and acquisition of the corresponding imaging. Next follows the analysis with the help of AI and human confirmation. AI-derived data is then taken into account against the clinical background in order to facilitate clinical synthesis, communication, and action. The quality control process offers a way to provide feedback concerning system performance, errors, and workflow is shown in Figure 1.

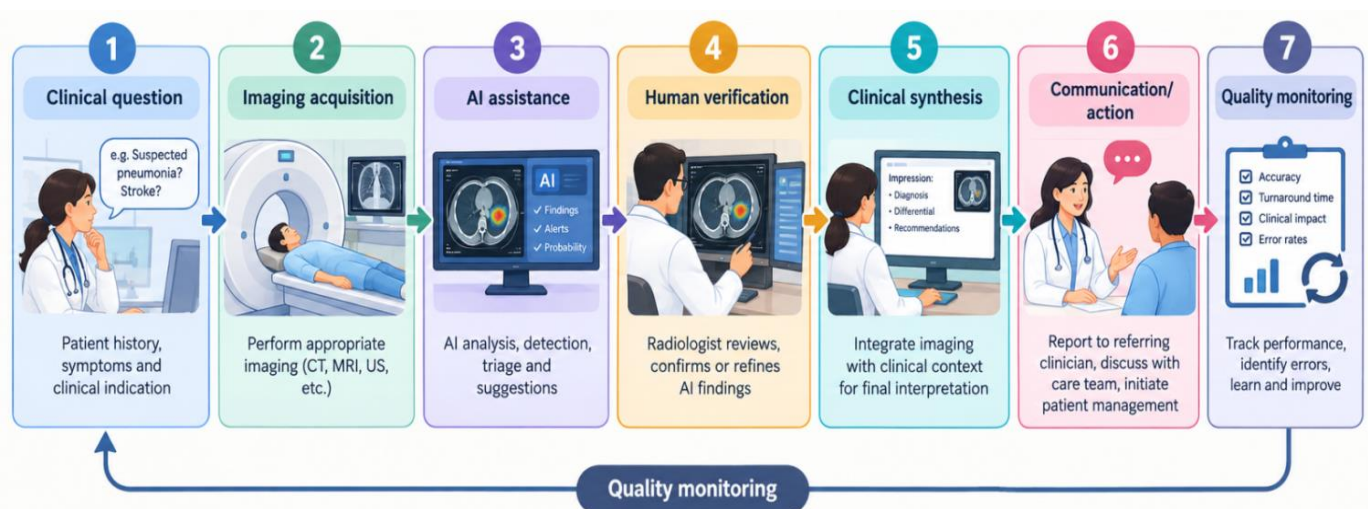


Figure 1. Graphical representation of A human-in-the-loop radiology pathway shows the human-in-the-loop workflow for AI-supported diagnostic imaging.

Potential Roles of Physician Assistants in Imaging

Creating Clinical Context

Clinical context is critical for appropriate imaging and interpretation. Within scope of practice, PAs may document patient's complaints, patient's clinical history, prior imaging, medication use, risk factors, examination results and urgency of clinical questions. Well-documented clinical information can help clinicians understand AI-derived results in the right context without considering algorithm output as a standalone piece of information (Geis et al., 2019; World Health Organization, 2021).

Patient Identification and Safety Check

PAs may be involved in patient identification, explanation of imaging procedure, documentation of pertinent clinical information, identification of safety issues, communication with imaging staff and post-procedure follow-up according to local protocols. The integration of AI technology should not eliminate these safety checks performed by humans.

Interaction with AI-Derived Findings

PAs may have access to AI-generated alerts, measurements and other initial information during routine work. These results must be considered as decision-support information but not as an independent diagnosis. PA may become aware of alert, evaluate it from clinical point of view within scope of practice, review radiological interpretation when available, communicate with the responsible clinician and escalate urgent or discrepant findings according to local policy. PAs should not verify AI algorithm independently (Geis et al., 2019; World Health Organization, 2021).

Communication and Care Coordination

PAs can assist in communicating pertinent information to patients and healthcare professionals after qualified interpretation is performed. It is particularly essential in case AI-powered summary notes or patient explanations are created. Human review is required since the system may not include certain contextual information, make unsupported claims or fail to communicate uncertainty (Lee et al., 2026).

Quality Improvement and Safety Reporting

PAs can participate in the process of quality improvement systems through documenting false positives/negatives, unintended alerts, interruptions in workflow, delayed escalations, inconsistencies between AI generated content and human interpretation, and difficulties with communication. It will be useful to AI governance groups involved in safety monitoring.

Patient Safety and Human Factors

False-Positives and False-Negatives

If the output is a false positive, it might trigger further investigations and/or patient alarm, but if the output is a false negative, this will be especially serious in time-critical disease. Human verification should therefore be built into the workflow. In the case of a negative output from AI, it should not take precedence over clinical judgment where patient history or other factors suggest further investigation.

External Validation and Dataset Shift

External validation is one of the most important requirements for clinical AI. According to the RAISE review, there was an average drop of 6% in external validation performance compared to the internal performance (Kelly et al., 2022). According to a 2025 systematic review, the performance of external validation has dropped despite internal performance being good, with some studies recording lower specificity (Suleman et

al., 2025). Scanner hardware differences, acquisition procedures, prevalence of disease, patient demographics, and workflows can influence performance.

Automation Bias and Cognitive Effects

Automation bias is the tendency to have undue confidence in computerized recommendations. In modern human-AI literature, there are three more issues – algorithmic aversion, deskilling, and changes in diagnostic reasoning (Kocak & Cuocolo, 2026). The training must then cover true predictions, false positive predictions, false negative predictions, uncertain predictions, low-quality imaging, and disagreement between AI and human experts.

Bias, Fairness and Generalizability

The AI algorithm is designed based on the data used to train the system. Possible sources of variability might involve demographics, diseases, scanner manufacturer, image acquisition protocol, hospital and image acquisition quality. In the 2025 generalisability study, it was shown that the external performance of an AI may be suboptimal in clinical practice and that there is a need for external validation in heterogeneous cohorts (Suleman et al., 2025).

Privacy, Cyber-security and Trustworthy AI

Imaging studies are comprised of sensitive data of the patients. Governance should be in place to address identifiers, imaging metadata, cloud-based processing, access control, cybersecurity, auditability and data management. The FUTURE-AI international guideline on trustworthy healthcare AI is described using fairness, universality, traceability, usability, robustness and explainability of AI algorithms (Lekadir et al., 2025).

Published Quantitative Evidence

From the quantitative evidence provided above, there is proof of the possible clinical utility of AI in diagnostic imaging as well as the possible limitations that should be noted when implementing this technology. A great share of published studies on AI in radiology has been retrospective, and studies that have performed an external validation of algorithms have shown that the performance of AI can get worse if the system is being tested in different conditions compared to those of its development. Nevertheless, there is evidence that AI-assisted cancer imaging shows higher pooled sensitivity and specificity than physician assessments alone in published papers, which proves its potential value as a decision-making aid. There is more proof of the expanding use of AI in diagnostic imaging from studies of point-of-care ultrasound by physician assistants, application of large language models to radiology reports, and randomized control trials are shown in Table 1.

Evidence	Published finding
Radiology AI studies that were retrospective in the RAISE review	98% (Kelly et al., 2022)
Average performance change in directly comparable external-validation studies	–6% (Kelly et al., 2022)
Algorithms showing some external-performance decrease	81% (External Validation of Deep Learning Algorithms for Radiologic Diagnosis, 2022)
AI-assisted cancer imaging pooled sensitivity	0.79 (Zhao et al., 2025)
Clinician-only cancer imaging pooled sensitivity	0.67 (Zhao et al., 2025)
AI-assisted cancer imaging pooled specificity	0.87 (Zhao et al., 2025)

Clinician-only cancer imaging pooled specificity	0.82 (Zhao et al., 2025)
PA POCUS eligible studies from retrieved records	30/717 (Zak & Monti, 2022)
LLM radiology-report studies included in 2026 scoping review	69 studies (Lee et al., 2026)
RCTs mapped in 2026 AI radiological diagnosis scoping review	9 RCTs (Yan et al., 2026)

Table 1. Selected published quantitative findings relevant to human-in-the-loop diagnostic imaging. Values originate from separate publications and are not institutional data.

The Role of Physician Assistant In Pocus Enabled By AI

POCUS acts as an excellent link between the practices of physician assistants and medical imaging. Scoping review on PA POCUS has revealed 30 relevant publications out of 717 total records, which showed that PAs are able to use a number of POCUS applications, whereas training and lack of equipment are among the main obstacles (Zak & Monti, 2022).

Newer evidence suggests that AI is now more and more incorporated into POCUS to assess image quality, identify anatomical structures, make measurements, etc., but there are still some limitations related to the low quality of acquired images as well as the influence of certain disease states on image quality (Kim et al., 2025). Moreover, the expert recommendations on POCUS curriculums for physician assistants have been recently released (Breunig et al., 2025). Thus, AI-assisted POCUS should stay within the scope of credentialing, training, and institutional guidelines.

Multidisciplinary Governance

AI usage must not be considered merely a technology department matter. A multidisciplinary governance team may involve radiologists, PAs, radiographers or radiologic technologists, referring physicians, medical physicists when appropriate, information technology specialists, data scientists, administration staff, quality and safety specialists, and legal experts.

The process of governance must set out how the AI system will be used, the patient population to which it is to be applied, validation processes, responsibilities of users, processes for escalating issues, documentation, privacy considerations, monitoring measures, and criteria to change or remove the system. The FUTURE-AI framework provides guidance on governance throughout the AI life cycle (Lekadir et al., 2025).

Hospital Implementation Framework

The hospital implementation framework offers a way of implementing AI in diagnostic imaging in a clinical sense. It stresses that the process needs to start from the identification of a clearly defined clinical need rather than adoption of the technology for its sake and then assessment of how well the system is performing in the specific clinical context. The need for proper training, professional accountability, human confirmation and discrepancy reporting becomes important in the process. Monitoring will help detect any changes in performance, workflow or safety considerations while periodic reassessment will ascertain if the system can still be used clinically and is shown in table 2.

Stage	Main question	Potential PA contribution	Safety checkpoint
1. Need identification	What clinical problem is being addressed?	Identify workflow problems and clinical context	Avoid technology-first adoption
2. Local validation	Does the system work in this setting?	Report workflow and clinical concerns	Assess local performance

3. Training	Do users understand limitations?	Complete role-specific education	Include failure scenarios
4. Deployment	Is the system safe in routine workflow?	Use outputs within defined scope	Maintain human verification
5. Monitoring	Does performance remain acceptable?	Report discrepancies and events	Monitor performance drift
6. Review	Should the system continue?	Participate in quality review	Continue, modify or retire based on evidence

Table 2. Proposed staged framework for implementing AI-supported diagnostic imaging in a hospital environment.

DISCUSSION

The findings suggest a complementarity approach where AI assists with computations and human professionals provide the context and make decisions about treatment. While AI support might help to enhance some diagnostic tools, the effectiveness of such an approach is variable, and the lack of external validation persists as a common issue (Zhao et al., 2025; Suleman et al., 2025). The most recent findings about the use of AI in the medical field indicate that the effectiveness of the technology depends on the manner in which it is incorporated (Kocak & Cuocolo, 2026; Kim et al., 2026).

Therefore, the contribution of PAs to radiology should not be perceived in terms of radiological diagnostics performed independently, but in terms of safety of the workflow and its coordination. PAs might assist with providing proper clinical context to the imaging professionals, performing patient-safety checks, noticing urgent issues or discrepancies, facilitating communication, and helping with incident reports. These actions will allow integrating the AI tool into the overall clinical workflow while retaining responsibility for the diagnosis to properly qualified professionals.

The approach is also aligned with the current direction of AI governance. The FUTURE-AI consensus calls for lifecycle considerations of fairness, universality, traceability, usability, robustness and explainability (Lekadir et al., 2025). Recent RCT findings show that AI can enhance selected diagnostic endpoints but the effect varies depending on the setting and there is still low specificity (Yan et al., 2026). Thus, implementation should start with defining the clinical problem, using local validation and monitoring, and having predefined escalation and withdrawal protocols.

The application of generative AI adds another layer of risk since language outcomes might seem plausible while being incomplete and sometimes false. The scoping review of 2026 on radiology reports showed that there are problems with validation and generalizability and also fewer than half of the studies in the review covered the issue of LLM stochasticity (Lee et al., 2026). The human review thus is especially critical for report generation, patient explanations and any other clinical communication from generative AI applications.

CHALLENGES AND LIMITATIONS

There are several limitations to the existing body of evidence. Most of the AI radiology literature still consists of retrospective studies and external validation is not always consistent. Additionally, there is far less direct evidence assessing PAs in the context of AI-supported radiology compared to radiologists. Furthermore, AI solutions have differences in terms of their intended use, training data, performance, regulation, and integration process.

Profession scope differs between different countries and institutions. The PA scope-of-practice proposed here should therefore be seen more as a conceptual framework rather than a general recommendation. Additionally, this paper represents a narrative review and not a systematic review or meta-analysis. Findings

presented in quantitative research should not be statistically combined and literature update performed selectively.

Future Research Priorities

Future research should not only focus on the accuracy of the algorithm but rather assess the performance and safety of human-AI teams. Key performance measures should include time to diagnosis, false negatives, unnecessary testing, reporting workloads, communication, delay of escalation and patient safety incidents. Multicenter prospective research studies using PAs, radiologists and other imaging experts would be very helpful.

For PAs specifically, research should consider competence in identifying limitations of AI, proper escalation, documentation and communication. Research should also consider how user interface design, AI output confidence levels, timing and discrepancy with clinical judgment influence decision making. When it comes to generative AI, prospective studies should focus on factual accuracy, hallucinations, reproducibility and the impact of human review.

PRACTICAL RECOMMENDATIONS

- The use of AI should be done as an assistive technology and not as an autonomous tool replacing clinical expertise and interpretation.
- The role of AI should be to augment clinical decision making through provision of extra information or analysis to aid clinical decision making, while final interpretation and decision making will be under human guidance.
- There should be clear indications of the purpose, intended population, and scope of performance of each AI.
- Users should be aware of the purposes, intended populations, and limitations of performance of each AI before it is implemented in a clinical practice.
- Validation should be done locally before clinical implementation of the AI.
- Each AI should go through validation using local patient population, imaging equipment, clinical practice, and workflow to see if it achieves its intended performance when used locally.
- Performance of the AI should be monitored after implementation for drift and clinically significant errors.
- Monitoring should detect any drifts or errors in performance of AI, as well as any discrepancies between AI output and clinical findings.
- PAs and other users should undergo role-appropriate AI education and competency assessment.
- The education should suit their duties and be such that users are adequately aware of the capabilities and proper application of AI-enhanced imaging modalities.
- The training should include cases with false positives, false negatives, uncertainty and technical failures.
- There should be difficult cases that highlight how AI might give inaccurate, inadequate or uncertain output and how such instances should be clinically handled.
- Information produced by the AI should not be taken as a final diagnosis.

- The output from the AI should be interpreted as decision support information and used together with the patient's history, examination findings and imaging along with clinical interpretation.
- There should be clear pathways for handling urgent or unexpected results.
- Workflows need to indicate how certain findings from AI systems should be escalated to radiologists, physicians or other responsible clinicians.
- AI-generated report wording and patient communications should be pre-communicated.
- The AI-generated wording needs to be reviewed for its accuracy, adequacy, and appropriateness before including them in the report and communicating to patients.
- Patient confidentiality, cybersecurity, auditability and data management must be considered during the implementation of AI.
- Provisions for protecting patient data, cybersecurity of the imaging data, tracking system activities, and policy management of data usage must be incorporated within the process of implementing the AI.
- PAs must take part in quality improvement and incident reporting in case of AI-enabled imaging.
- The PA's participation is essential in uncovering any workflow issues, any problems in communication, abnormal behavior of the AI, and the safety issues that may emerge from routine clinical practice.
- The clinical responsibility must be assigned to the properly authorized professionals.
- AI cannot assume the clinical responsibility, and the accountability for reviewing, interpreting, communicating and taking action on the clinical information must be clearly established.

CONCLUSION

The human-in-the-loop concept of using AI is a useful conceptual approach to integrating artificial intelligence into diagnostic imaging while maintaining professional judgement and patient-focused care. Emerging evidence suggests that using AI may help to enhance certain diagnostics, but external effectiveness may suffer, and the impact on clinical practice may differ according to the setting, disease and work process (Suleman et al., 2025; Zhao et al., 2025; Yan et al., 2026).

There is a potential contribution by Physician Assistants in terms of documenting clinical context, preparing patients, communicating, coordinating care, escalating and performing quality control activities as long as all these activities stay within professional and organizational boundaries. The growing body of literature on human-AI collaboration seems to confirm that the safety of AI-assisted radiology is more about interaction of technology, humans, processes and governance than just accuracy of the algorithm (Kocak & Cuocolo, 2026; Kim et al., 2026). Thus, responsible use of AI in radiology implies validation, education, documentation, governance, privacy protection and continuous monitoring on the local level.

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Ethical Considerations

No ethical approval was needed in this paper because it is a narrative review of existing literature and thus does not contain any original research involving humans or animals.

Data Availability

There was no creation or analysis of data in this narrative review as it solely relies on evidence from existing literature.

Conflict of Interest

No conflict of interest among authors

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REFERENCES

1. Baethge, C., Goldbeck-Wood, S., & Mertens, S. (2019). SANRA—a scale for the quality assessment of narrative review articles. *Research Integrity and Peer Review*, 4, 5. <https://doi.org/10.1186/s41073-019-0064-8>
2. Breunig, M., Bafuma, P., & Bludorn, J. (2025). Point-of-care ultrasound curricula in physician assistant programs: Recommendations from a panel of experts. *Journal of Physician Assistant Education*, 36(3), e240–e247. <https://doi.org/10.1097/JPA.0000000000000663>
3. External Validation of Deep Learning Algorithms for Radiologic Diagnosis: A Systematic Review. (2022). *Radiology*. PMID: 35652114.
4. Geis, J. R., Brady, A. P., Wu, C. C., Spencer, J., Ranschaert, E., Jaremko, J. L., Langer, S. G., Kitts, A. B., Birch, J., Shields, W. F., van den Hoven van Genderen, R., Kotter, E., Gichoya, J. W., Cook, T. S., Morgan, M. B., Tang, A., Safdar, N. M., & Kohli, M. (2019). Ethics of artificial intelligence in radiology: Summary of the joint European and North American multisociety statement. *Radiology*, 293(2), 436–440. <https://doi.org/10.1148/radiol.201919158>
5. Grant, M. J., & Booth, A. (2009). A typology of reviews: An analysis of 14 review types and associated methodologies. *Health Information and Libraries Journal*, 26(2), 91–108. <https://doi.org/10.1111/j.1471-1842.2009.00848.x>
6. Kelly, B. S., Judge, C., Bollard, S. M., Clifford, S., Healy, G. M., Aziz, A., & others. (2022). Radiology artificial intelligence: A systematic review and evaluation of methods (RAISE). *European Radiology*, 32(11), 7998–8007.
7. Kim, J., Adams, L. C., Wiestler, B., & Hedderich, D. M. (2026). Human-AI collaboration in radiology: The blind spots. *Radiology: Artificial Intelligence*, 8(5), e260325. <https://doi.org/10.1148/ryai.260325>
8. Kim, J., Maranna, S., Watson, C., & Parange, N. (2025). A scoping review on the integration of artificial intelligence in point-of-care ultrasound: Current clinical applications. *American Journal of Emergency Medicine*, 92, 172–181. <https://doi.org/10.1016/j.ajem.2025.03.029>
9. Kocak, B., & Cuocolo, R. (2026). Human–AI interaction and collaboration in radiology: From conceptual frameworks to responsible implementation. *Diagnostic and Interventional Radiology*, 32(5), 535–547. <https://doi.org/10.4274/dir.2026.263780>
10. Lee, R. C., Hadidchi, R., Coard, M. C., Rubinov, Y., Alamuri, T., Liaw, A., Chandrupatla, R., & Duong, T. Q. (2026). Use of large language models on radiology reports: A scoping review. *Journal of the American College of Radiology*, 23(3), 437–454. <https://doi.org/10.1016/j.jacr.2025.10.005>
11. Lekadir, K., Frangi, A. F., Porras, A. R., Glocker, B., Cintas, C., Langlotz, C. P., & FUTURE-AI Consortium. (2025). FUTURE-AI: International consensus guideline for trustworthy and deployable artificial intelligence in healthcare. *BMJ*, 388, e081554. <https://doi.org/10.1136/bmj-2024-081554>

12. Mongan, J., Moy, L., & Kahn, C. E., Jr. (2020). Checklist for artificial intelligence in medical imaging (CLAIM): A guide for authors and reviewers. *Radiology: Artificial Intelligence*, 2(2), e200029. <https://doi.org/10.1148/ryai.2020200029>
13. Schuur, F., Rezazade Mehrizi, M. H., & Ranschaert, E. (2021). Training opportunities of artificial intelligence (AI) in radiology: A systematic review. *European Radiology*, 31(8), 6021–6029.
14. Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, 333–339. <https://doi.org/10.1016/j.jbusres.2019.07.039>
15. Suleman, M. U., Mursaleen, M., Khalil, U., Saboor, A., Bilal, M., Khan, S. A., Subhani, M. A., Hussnain, M. A., Tabassum, S. N., & Tahir, M. (2025). Assessing the generalizability of artificial intelligence in radiology: A systematic review of performance across different clinical settings. *Annals of Medicine and Surgery*, 87(12), 8803–8811. <https://doi.org/10.1097/MS9.0000000000004166>
16. Tejani, A. S., Klontzas, M. E., Gatti, A. A., et al. (2024). Checklist for artificial intelligence in medical imaging (CLAIM): 2024 update. *Radiology: Artificial Intelligence*, 6(4), e240300.
17. Yan, Y., Liu, C., Fu, H., Xu, K., & Xu, H. (2026). Efficacy evaluation of artificial intelligence in radiological imaging diagnosis based on randomized controlled trials: A scoping review. *European Radiology*. Advance online publication. <https://doi.org/10.1007/s00330-026-12715-0>
18. Zak, C. L., & Monti, J. D. (2022). PAs and point-of-care ultrasound: A scoping review. *JAAPA*, 35(4), 43–50.
19. Zhao, D., Packer, T., Jie, X., Shahid, M., Oke, J., & Plüddemann, A. (2025). Diagnostic accuracy of artificial intelligence-assisted radiology assessment of cancer: A systematic review. *BJR|Artificial Intelligence*, 2(1), ubaf016. <https://doi.org/10.1093/bjr/ubaf016>
20. World Health Organization. (2021). Ethics and governance of artificial intelligence for health: WHO guidance. World Health Organization.