Overview of Radiology Artificial Intelligence: Latest Progress

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Over the past decade, artificial intelligence (AI) has become increasingly integrated into the practice of radiology. Use cases for pixel-based and non–pixel-based tools exist. As of fall 2025, there are more than 400 FDA-cleared radiology AI applications [1]. New technologies are continuously being developed. Nevertheless, deployment of AI into the clinical workflow continues to face challenges. The definitions of AI, machine learning, deep learning, and natural language processing (NLP) are now well established. Newer technologies, such as generative AI and foundation models (FMs), are rapidly developing. Figure 1 summarizes these definitions.

AI is frequently positioned as a partial remedy to clinical workflow, offering the possibility of triage, automation, and decision support to improve turnaround times and reduce diagnostic errors. Another vital element of the radiology AI landscape is the acceleration of cross-disciplinary innovation. Advances in computer vision, NLP, and multimodal learning are converging in ways that blur the traditional boundaries between pixel-based and non–pixel-based applications, which we will discuss in the latter part of this chapter. The shift from narrow, task-specific AI toward FMs and generative AI represents a paradigm change, with potential to reconfigure how radiologists interact with both images and clinical data.

In the setting of the ever-growing mismatch between radiology volumes and the size of the radiology workforce, AI is repeatedly touted as a solution that will bring increased efficiency and automation to the specialty. In this chapter, we will discuss the current state of radiology AI, various use cases and applications, challenges in implementation, and broader ethical and societal considerations.

Pixel-Based Use Cases

For most of the past decade, clinical radiology AI has been focused on addressing pixel-based problems. These so-called "narrow" use cases for AI often identify findings on an imaging examination, such as intracranial hemorrhage, pulmonary embolism, or coronary calcification [2]. These models are typically convolutional neural networks (CNNs) that are trained using supervised learning, a process through which the algorithm learns associations by being exposed to multiple labeled examples, also known as training data. Once trained, the resulting model may be validated on a second set of cases to refine performance iteratively. Ultimately, the final model is tested on a separate set of cases to evaluate its performance objectively.

Another frontier in the field has been in the radiomics space, which has also paved the way for radiogenomics: that is, integrating imaging data with genomic, proteomic, and clinical information [3]. These approaches extend the precision medicine paradigm by linking noninvasive imaging features with underlying biologic processes. Although radiogenomics is still confined mainly to research, early results suggest that radiogenomic models may someday help stratify patients for targeted therapies, predict treatment response, and monitor disease progression longitudinally. Such applications illustrate the trajectory from narrow detection tasks toward broader decision-support roles.

FMs, a newer AI technique, are emerging rapidly [4]. Trained on vast and multimodal datasets, they can be adapted to many downstream tasks with minimal fine-tuning. This scalability offers opportunities for more generalizable and flexible tools, while also introducing challenges around data provenance, computational cost, and interpretability. Previously conceptual tasks, such as draft reporting, have been made feasible by FMs.

Non–Pixel-Based Use Cases

NLP has been applied in radiology for decades, primarily to extract discrete data elements from unstructured radiology reports [5]. Conventional NLP is rule-based and requires substantial effort to understand the variety within the documents to be processed and establish a sufficiently robust set of rules that can accommodate this variety. By comparison, newer AI approaches to text processing have substituted rules for training data. Networks such as long short-term memory networks (LSTMs) performed well on various radiology report tasks, such as the

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detection of abnormalities [6] or follow-up recommendations [7]. Bidirectional encoder representations from transformers (BERT) models have further improved the capability and efficiency of NLP for radiology tasks, such as anatomic classification and error-checking [8, 9].

Beyond structured information extraction, non–pixel-based AI is increasingly being applied to workflow optimization and quality assurance [10]. Systems can automatically flag incomplete reports, detect inconsistencies between clinical history and imaging findings, or highlight critical results for expedited review. As these tools mature, they may help reduce administrative burdens on radiologists, while also improving the transparency and accessibility of imaging information [11].

Generative AI and FMs

Over the past 3 years, generative AI has introduced new capabilities to radiology [12]. Broadly, generative AI refers to models that learn data distributions and create new outputs (such as images or text) that mimic real examples. In radiology, diffusion models can synthesize realistic CT or MR images for training, and transformer-based large language models (LLMs) can generate structured reports or summarize findings. These systems shift radiology AI from simple detection toward tools that can create, reason, and support multiple stages of the imaging workflow.

LLMs have realized multiple non–pixel-based use cases for radiology AI [13]. There has been an increased number of publications in this space since the advent of the GPT model from OpenAI (Fig. 2). The literature contains many examples that equal or surpass the performance of LSTM and BERT models with substantially less effort on the part of domain experts to label data for training. More recently, they have also been applied to higher-level tasks, including automated impression drafting, quality assurance, and even generating patient-friendly summaries. These applications show the ability of LLMs to decrease manual work, standardize reporting, and extend the impact of radiology information beyond the interpreting physician [14].

This multimodal approach marks a shift from single-task, narrow AI toward

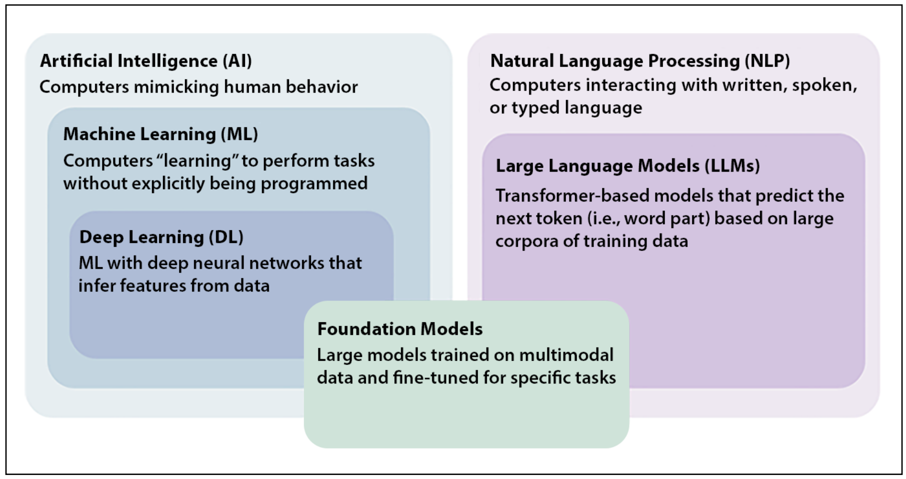

Fig. 1—Flowchart shows artificial intelligence concepts, definitions, and relationships, some of which have also been discussed by Steinkamp and Cook [46].

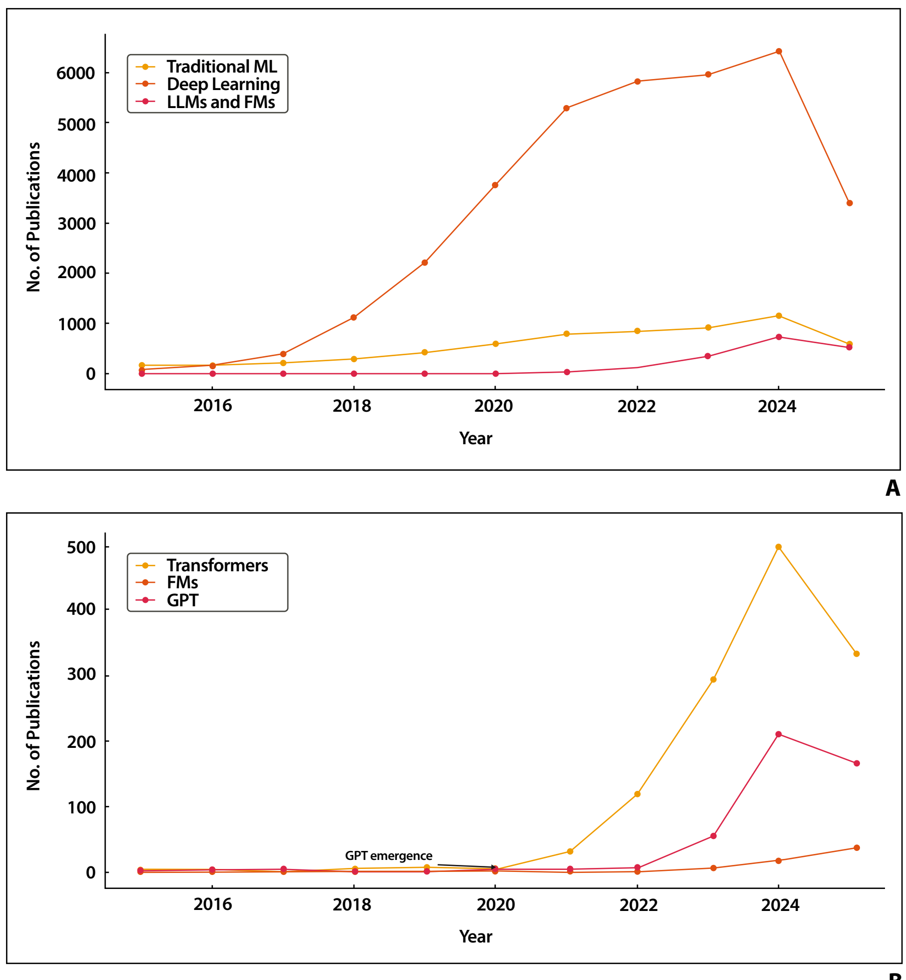

Fig. 2—Graphs show trends in artificial intelligence (AI) publications in radiology from 2015 to 2025. ML = machine learning, LLM = large language model, FM = foundation model.
A, Growth of radiology AI publications is shown by method, revealing peak of deep learning and recent rise of LLMs and FMs.
B, Increases in publications focused on transformers and GPT (OpenAI)-based models illustrate rapid shift toward generalist and generative AI.

generalist systems that can adapt across domains. FMs have shown early success in cross-modality applications such as classifying both CT and MR images, integrating imaging with clinical notes, and enabling zero-shot or few-shot learning where minimal task-specific data are available [15]. Their scalability raises the possibility of deploying a single adaptable model across multiple sites and use cases, thereby reducing the need to train separate models for each task. At the same time, these models pose challenges in terms of transparency, reproducibility, and the significant computational resources required for training and fine-tuning.

Implementation and Governance

Robust governance frameworks are critical to safe radiology AI deployment. Institutions increasingly rely on multidisciplinary committees and oversight processes. Radiologists, information technology (IT) experts, data scientists, ethicists, and administrators guide decisions around evaluation, adoption, and monitoring [16–18]. Oversight can take different forms: human-in-the-loop approaches require radiologists to validate each AI output, whereas human-on-the-loop models allow AI to operate with more autonomy, subject to supervisory checks (Fig. 3). Choosing the appropriate oversight model depends on the level of clinical risk, workflow integration, and institutional readiness. Fully autonomous AI remains a theoretic concept in radiology. Continuous postdeployment monitoring is also essential. Both FDA-regulated and non–FDA-regulated tools can degrade or drift when applied to new populations, devices, or workflows [19, 20]. Continuous monitoring helps identify deviations from expected performance and ensure patient safety [21].

At the same time, human factors must be addressed: clinicians may be susceptible to automation bias, an overreliance on AI in lieu of clinical judgment, or to algorithm neglect, the dismissal of reasonable AI outputs due to skepticism about the technology [22]. Furthermore, concerns have been raised about deskilling, where sustained dependence on AI may erode diagnostic expertise [23]. Together, these issues underscore the importance of combining technical validation, continuous monitoring, and deliberate strategies to preserve human expertise. Therefore, the actual implementation of AI in radiology lies in the Goldilocks zone of governance, monitoring, and efficient usage, which increases workflow efficiency and reduces burden on clinicians.

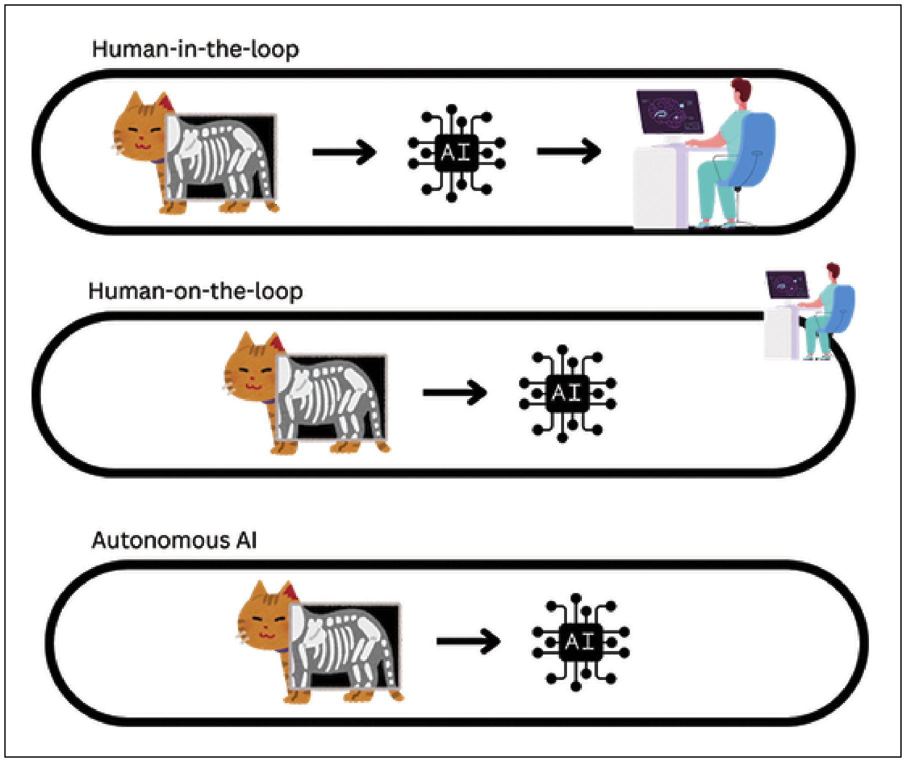

Fig. 3—Schematic shows implementation approaches for artificial intelligence (AI). (Icons © Canva.com, used with permission)

Regulation, Policy, and Reimbursement

The regulatory environment for radiology AI remains complex and fragmented. In the United States, most models are cleared through the FDA's 510(k) pathway, and some high-impact tools may qualify for the breakthrough designation or follow the emerging predetermined change control plan framework [24]. By contrast, LLMs are not yet regulated in the United States, whereas the United Kingdom and Europe are pursuing structured oversight [25, 26]. The European Union's Artificial Intelligence Act provides a risk-tiered framework, categorizing medical AI systems as high-risk and subjecting them to stricter evaluation [27, 28].

Policy considerations are closely tied to reimbursement. In the United States, temporary coverage mechanisms such as the New Technology Add-on Payment (NTAP) have promoted early adoption of AI, but long-term sustainability will likely depend on the approval of new category 1 CPT codes [29]. Meanwhile, the FDA's oversight process for imaging AI continues to evolve, balancing innovation with the need for robust safety and performance standards [30, 31]. These intersecting issues underscore the importance of regulatory clarity and reliable reimbursement pathways in enabling the responsible scaling of radiology AI.

Medicolegal, Ethical, and Societal Considerations

The *Spider-Man* franchise has taught us that "with great power comes great responsibility" [32]. Radiology AI raises pressing questions of bias, fairness, and accountability. Algorithms trained on incomplete or skewed datasets risk amplifying existing disparities for underrepresented populations or introducing new disparities for populations underrepresented in the training data [33, 34]. Without deliberate design and monitoring, deployment could exacerbate inequities rather than alleviate them. Patients' views also matter: while many express openness to AI in their care, trust depends on transparency and assurance that AI complements rather than replaces clinical judgment [35].

Perceptions of AI among physicians remain mixed. Some worry that reliance on AI undermines professional identity, while others see it as a tool to extend expertise [36]. In medicine outside of radiology, ambient scribe technology has revolutionized ambulatory clinician-patient interactions [37]. AI as an "inboxologist" has further decreased the workload of overextended clinicians who have to respond to patient messages after spending the day caring for patients [38]. As a result, AI literacy among both practicing physicians and medical students is becoming a core component of undergraduate and graduate medical education [39].

Medicolegal concerns add further complexity: when errors occur, responsibility remains poorly defined, with liability often defaulting to the radiologist [40]. These unresolved questions have significant implications for health equity. If AI systems are adopted unevenly (i.e., accessible in well-resourced centers but absent in underserved ones), they risk widening gaps in care. Ethical deployment, therefore, demands not only technical rigor but also policy frameworks that safeguard fairness, accountability, and equitable access across diverse patient populations.

Policy frameworks to safeguard fairness, accountability, and equitable access across diverse patient populations are also needed. With the rise of generative AI and generalist FMs, governance must evolve beyond single-task validation to continuous oversight across modalities and contexts. Without such guardrails, the very systems designed to democratize radiology risk entrenching new forms of inequity.

Looking to the Future

The future of radiology AI will be shaped by increasing autonomy for narrow tasks, the maturation of FMs, and integration into education and training. While fully autonomous AI remains limited, advances in FMs suggest a trajectory toward systems capable of drafting complete reports, reasoning across multimodal data, and supporting clinical decision-making at scale [4, 41, 42]. Educating residents to critically evaluate and properly use these tools will be essential in preserving human expertise and safeguarding against overreliance [43]. Beyond local implementation, the broader challenge is to ensure that these innovations translate on the global scale. If deployed thoughtfully, AI could help address workforce shortages, expand access to imaging in resource-limited settings, and narrow disparities in care [44]. Still, without deliberate governance, the same technologies risk reinforcing inequities, underscoring the responsibility of radiologists to shape an AI future that is both innovative and equitable.

Conclusion

AI is actively transforming the practice of radiology through a variety of pixel-based and non–pixel-based use cases. Challenges in implementation and reimbursement exist, and the specialty continues to explore how this new technology can address the workforce-workload mismatch as well as other points of friction in the workflow. Nevertheless, it is our collective responsibility to ensure that this new technology is deployed in a manner that is safe and effective for our patients and to identify and mitigate biases that may adversely impact care delivery for certain patient subgroups. As this new technology continues to evolve, radiologists must play an active role in its development and evaluation. As AI continues to evolve, radiologists must remain active participants in its development, evaluation, and governance. As Atul Gawande once observed, "Better is possible. It does not take genius. It takes diligence. It takes moral clarity. It takes ingenuity" [45].

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