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Physician-in-the-Loop Active Learning in Radiology Artificial Intelligence Workflows: Opportunities, Challenges, and Future Directions

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Abstract

Artificial intelligence (AI) is being explored for a growing range of applications in radiology, including image reconstruction, image segmentation, synthetic image generation, disease classification, worklist triage, and examination scheduling. However, training accurate AI models typically requires substantial amounts of expert-labeled data, which can be time-consuming and expensive to obtain. Active learning offers a potential strategy for mitigating the impacts of such labeling requirements. In contrast with other machine-learning approaches used for data-limited situations, active learning aims to produce labeled datasets by identifying the most informative or uncertain data for human annotation, thereby reducing labeling burden to improve model performance under constrained datasets. This Review explores the application of active learning to radiology AI, focusing on the role of active learning in reducing the resources needed to train radiology AI models while enhancing physician-AI interaction and collaboration. We discuss how active learning can be incorporated into radiology workflows to promote physician-in-the-loop AI systems, presenting key active learning concepts and use cases for radiology-based tasks, including through literature-based examples. Finally, we provide summary recommendations for the integration of active learning in radiology workflows while highlighting relevant opportunities, challenges, and future directions.

Highlights

- Active learning aims to maximize AI model performance while reducing radiologists' labeling burden
- Radiology workflows may incorporate active learning to achieve physician-in-the-loop AI implementation.
- Ethical standards, model accuracy, effective system integration, and continued education of radiologists and trainees will all be essential for clinical use of active learning AI.

Introduction

Artificial intelligence (AI) is being explored for a growing range of applications in radiology, including image reconstruction, image segmentation, synthetic image generation, disease classification, worklist triage, and examination scheduling [1–4]. The development and deployment of high-quality AI models for radiology-relevant tasks could help ameliorate limitations in imaging access and global radiologist shortages. Leveraging collaborative partnerships between radiologists and AI solutions within clinical workflows, these models may expand the impact of medical imaging, for example through segmentation-based outcome predictions [5].

Traditional supervised learning techniques require fully labeled datasets [6,7], with performance closely tied to the quantity of available training data [7]. Such datasets may be challenging and expensive to obtain in clinical contexts, in part due to radiologists' limited time to perform large volumes of manual labeling. For example, the time needed to label a single image can range from minutes to hours, depending on case complexity and the nature of the software tool used for the task [8]. Open-source datasets (e.g., The Cancer Imaging Archive) require substantial resources to label, with labeling of a single dataset potentially taking years to complete [9,10]. Model training is also hindered by restricted access to clinical data and other patient information [11]. Patient privacy concerns and institutional policies may create further barriers to necessary data sharing [12]. These issues can slow AI innovation, as large high-quality datasets are essential for algorithms' development and assessment [13].

Active learning offers a potential strategy for mitigating the impacts of labeling requirements as well as challenges from data and code sharing restrictions. In contrast with other machine-learning (ML) approaches used for data-limited situations—such as transfer learning, which applies existing models trained on large-scale datasets to a separate task, and self-supervised learning, which trains models on unlabeled data [14]—active learning aims to produce labeled datasets by identifying the most informative or uncertain data for human annotation, thereby reducing labeling burden to improve model performance despite constrained datasets [15,16]. Active learning is an increasingly relevant topic for radiology, although existing review articles on this topic have focused mainly on the method's technical aspects [15,17–19], rather than on its practical integration into radiology AI workflows.

This article explores the application of active learning to radiology AI, focusing on the roles of active learning in reducing the resources needed to train radiology AI models and in enhancing physician-AI interaction and collaboration. We discuss how active learning can be incorporated into radiology workflows to promote physician-in-the-loop AI systems, presenting key active learning concepts and use cases for radiology-based tasks, including through literature-based examples. We provide summary recommendations for the integration of active learning in radiology workflows while highlighting relevant opportunities, challenges, and future directions.

Active Learning Methods

Definition

In supervised ML, models are trained using a labeled dataset, learning the relationship between the data and associated labels [6]. By contrast, unsupervised ML models are trained on unlabeled datasets with the goal of automatic detection of relationships in the data [6]. Unsupervised models then generate decisions or hypotheses based on patterns learned from the data [20]. Semi-supervised methods, including active learning, are a hybrid of the two approaches and use both labeled and unlabeled data [21].

The main goal of active learning is to accelerate model training by strategically selecting data for annotation [15]. Specifically, active learning ranks unlabeled samples by their potential utility or informativeness, queries an expert (so-called "oracle") to provide labels for the most valuable samples, and updates the model using newly labeled data [15,16,22]. Models can be updated by retraining with all available labels or by fine-tuning using new labels alone [16]. Compared to supervised learning, active learning may significantly reduce the labeling workload for clinical users [16], ensuring that models learn efficiently from smaller curated datasets. By minimizing redundancy and focusing efforts on ambiguous or uncertain cases, active learning enhances both the cost-effectiveness and performance of ML models in clinical applications.

Training Strategies

Active learning can be performed using several strategies; common strategies include membership query synthesis, stream-based selective sampling, and pool-based sampling (Fig. 1).

Membership query synthesis leverages a ML model to generate synthetic data from the distribution of currently available data and queries an oracle for their labels [15,16]. For instance, while training a model to classify lung nodules on CT scans, a generative algorithm might produce a synthetic image with ambiguous features. Obtaining labels for these more challenging cases can aid model refinement. This strategy may produce unrealistic images [16] that are less clinically relevant, hence limiting the model's real-world performance. It may be impractical for radiologists, facing substantial time constraints, to devote effort to labeling synthetic images. Nonetheless, synthetic images displaying ambiguous or rare features could be useful for trainees in certain educational contexts.

Stream-based selective sampling considers a continuous stream of unlabeled data to determine whether to request a label from the oracle based on an informativeness measure calculated by the model [15,16]. One approach for this type of sampling is for the AI algorithm to prioritize the annotation of data or images in which the algorithm is the most uncertain about its prediction. For example, in detecting tumors on brain MRI, the model may request labels only for examinations in which the likelihood of a tumor is difficult to ascertain. Although stream-based sampling offers computational efficiency, this approach may cause the model to potentially miss patterns in the overall data distribution [15,16].

Pool-based sampling assumes access to a large pool of unlabeled data from which the most informative samples are selected for labeling [15,16]. The algorithm evaluates and ranks the entire dataset before selecting the most informative data. For instance, given a large database of unlabeled chest radiographs, the algorithm could select images that contain rare or complex pathologies for radiologist annotation. Although pool-based sampling allows for more global optimization by considering the entire dataset's distribution, it requires greater memory and computational resources [16]. Such a strategy that accounts for the whole patient population and selects examinations that may depict rare or complex pathologies for further radiologist review of model-generated labels not only facilitates model training but could help to triage the review process by selecting uncertain cases from the overall pool of cases. Overall, pool-based sampling often provides the optimal balance between clinical relevance and model performance despite its higher computational demands.

Active learning is commonly employed in an offline manner in various existing research settings. Specifically, models are trained on labeled data until some performance threshold is reached, and additional data points are then selectively labeled for further refinement. However, in AI-assisted clinical workflows, especially those aiming for continuous improvement, active learning could be implemented in a near real-time manner, whereby new cases are periodically queried for annotation and immediate integration into the training process. This approach may involve continuous re-training or fine-tuning of the active learning model after radiologists complete their review of new cases or batch of cases. The U.S. FDA has released guidelines concerning the use of software as a medical device (SaMD) in healthcare [23,24]; such statements describe a proposed regulatory framework for SaMD, including guiding principles for transparency and recommendations for iterative improvement of algorithms for AI-enabled devices. A data management plan should be developed that addresses collection and incorporation of new data, protocols for re-training and implementing modifications to AI devices, and assessment of the impact of such modifications. Manufacturers should document any changes and submit for FDA premarket review if such changes lead to new uses for the algorithm. A continuous learning approach for AI medical devices requires adherence to previously described regulatory frameworks and other considerations [25].

AI-Assisted Physician-in-the-Loop Radiology Workflows With Active Learning

A typical radiology workflow (Fig. 2) relies on multiple interconnected computer and information systems. Understanding both the general structure and functionality of these systems is crucial for identifying where active-learning-based tools can be effectively integrated. The PACS serves as a key infrastructure component within clinical workflows, offering a natural integration point for AI models [26]. Coordination with the PACS is facilitated through standards for data transfer and exchange between systems, including DICOM, Fast Healthcare Interoperability Resources, and Health Level 7 [27]. For AI tools to be integrated into clinical workflows, particularly those employing active learning techniques, they should conform to established standards and provide results in a timely fashion (i.e., by the time of radiologist review).

A meta-analysis found that the integration of AI into PACS yields improvements in diagnostic accuracy and reductions in diagnostic times by up to 90% [28]. That meta-analysis described the leveraging of AI within PACS for such tasks as optimizing CT protocols, automating image annotation, and enabling structured reporting [28]. Despite the potential benefits, widespread PACS adoption of AI remains limited due to such factors as integration complexity and insufficient tools to support automation of storage, retrieval, and distribution of patient images in a secure and reliable manner [28].

The involvement of radiologists in the active learning paradigm is an example of a human-in-the-loop system, entailing integration and collaboration between humans and AI models [22]. In the present context, interactions between radiologists and AI models more specifically represent a physician-in-the-loop system. Importantly, in such systems, the interaction between the physician and the AI model introduces specific considerations, namely that the interactions must be feasible, efficient, and integrated within existing clinical workflows. Incorporation of physician-in-the-loop methods in radiology workflows can help increase AI systems' transparency, interpretability, and explainability [16,29].

Physician-in-the-loop AI does not necessarily require improving the AI model itself; at a minimum, it may simply involve physicians' use of a platform to audit and modify AI outputs when needed. At a deeper level, though, this framework can be used to cross-inform the AI model for further improvements (i.e., interactive learning), so that the model is not only supervised, but also improved. Interactive learning involves a closer relationship between users and AI systems, allowing users to contribute to the iterative learning process [22]. Active learning is a primary technique to enable such interactive learning.

Active learning, by design, relies on human expertise, which may involve delineating ROIs and accepting or rejecting model-generated reports. In radiology, this approach translates to a physician-in-the-loop workflow, whereby radiologists provide annotations that directly refine model performance. In turn, the final model may serve a useful clinical purpose by generating interpretable predictions that guide clinical decision-making. For example, models using various quantitative imaging features have been used to predict outcomes in lymphoma, lung cancer, and colorectal cancer [30–32], although requiring image segmentation by radiologists. An active learning AI tool deployed to a radiology workflow may be more successful in enabling these predictive models' integration by minimizing the radiologist efforts required for model training. In this new active-learning-enabled radiology workflow, radiologists would directly participate in the model training process by reviewing and modifying only the most uncertain model results.

A multisociety statement published in 2024 on the incorporation of AI into radiology practice suggests that "the integration of AI algorithms into the radiology workflow is key to ensure their safe and consistent operation," highlighting the importance of a streamlined interface [33]. AI developers are encouraged to produce solutions that address unmet clinical needs, outperform existing tools, and maintain transparency and explainability [33]. These recommendations also apply to active learning tools. Figure 3 provides an example of a potential active learning process between the radiology workflow and active learning cycle, wherein radiologists can provide interactive feedback to the AI model during their consideration of each patient, for example accepting or rejecting model-generated results and modifying annotations. The radiologist's feedback is then used to fine-tune and update the model in a process overseen by AI scientists. Quality assurance and information technology (IT) staff provide additional regular maintenance, quality control, and technologic support for the AI tool's use.

Active learning AI use may also cause disruptions to the radiology workflow, as the time that radiologists spend evaluating, modifying, and providing feedback on AI predictions impacts efficiency even in active learning workflows. Two prospective randomized observational studies found that a significant portion (37.1% and 43.8%) of radiologists' time in the reading room was occupied by non-image interpretive tasks, including several task-switching interruptions each hour [34,35]. Frequent AI use can increase the risk of radiologist burnout [36], indicating a need to monitor for workplace stress resulting from AI use. Current reimbursement models do not compensate radiologists for the time spent providing labels; thus, other incentives may be needed for radiologists to interact with active learning AI tools. Current AI training opportunities for radiologists are often offered as short standalone lectures or courses, highlighting a need for better-developed programs for radiologists to learn the practical applications of AI in clinical work [37]. Specifically, AI should be taught through more robust and engaging workshops that include training on active learning tools while providing continuing medical education credits for participants [38].

At present, various radiology AI tools are commercially available, as outlined by van Leeuwen et al. [39]. The vendors frequently target just common clinical use cases, not addressing potentially overlapping functionalities; this issue may lead to challenges in clinical practice relating to workflow confusion and difficulties in performing comparative assessments and other integration tasks. Rigorous evaluation and validation of AI tools should be completed for specific clinical contexts using defined criteria such as ease of use, clinical impact, and integration feasibility.

To our knowledge, no or few current radiology AI products aim explicitly to involve active learning. Furthermore, information regarding the development of commercial AI tools may be unclear, with only 36% of commercial products supported by peer-reviewed studies [39, 40]. It is important for AI tools to be able to receive feedback in order to enable model refinement that counteracts expected decreases in performance over time as data or patient populations change; such feedback instead allows model performance to be maintained or even improved [33]. The mechanism used to acquire radiologist feedback for active learning AI tools must be considered. Feedback that can be collected quickly and easily should be prioritized in order to minimize radiologist efforts and decrease workflow disruptions. For instance, gaze tracking software [41], which identifies in real-time the portion of the image on which the radiologist is focusing, can be used to improve segmentation efficiency. Figure 4 provides an example of segmentation using gaze tracking in 3D Slicer software [42–45].

Existing Active Learning Approaches in Radiology

Researchers have aimed to integrate active-learning-like tools into various elements of radiology practice. A key challenge is the integration of AI tools into PACS and other systems in way that enhances the user experience. AI systems that have been developed with the intent of deployment in radiology settings include tools that enable radiologists to request AI image processing and tools that enable radiologists to provide feedback on AI-generated findings [46,47]. These tools have used diverse imaging data, including CT of the head, chest, or abdomen, and MRI of the kidneys [46–48]. The use of familiar interfaces improves radiologists' ease of use, while compliance with healthcare privacy standards, including HIPAA, is critical to ensure secure results visualization [46,47]. Use of user-friendly interfaces and feedback mechanisms for integration of AI tools greatly aids true active learning systems, empowering radiologists in such tasks as issuing requests for image processing by an AI tool and providing targeted annotations for model training.

Collection of user feedback is essential for evaluating AI tools. Juluru et al. [49] used a five-point Likert scale to assess satisfaction among radiology attendings and trainees, while Kanakaraj et al. [46] highlighted feedback forms addressing utility and understandability as a future need [46,49].

In one study, radiologist feedback was used to reduce false positives for an AI system designed to detect brain metastases [48]. Optimal collaboration requires active radiologist engagement, including for example soliciting radiologists' feedback, allowing radiologists to adjust results, developing tools for radiologists to evaluate AI workflows, and involving radiologists in AI guideline creation [46,47,49,50].

Studies examining active learning tools demonstrate that labeling a proportion of the full dataset (from approximately 5% to 50%) still achieves comparable accuracy to supervised models trained on fully labeled datasets [10,51,52]. Additionally, fine-tuning models using active learning approaches may reduce labeling efforts by over 80%, facilitating transfer learning [53]. Models that learn passively by randomly selecting data for labeling may not acquire data points that cover the whole range of cases, whereas an active learning strategy may select data that are highly representative of the whole dataset [54]. If labeling efforts can be reduced while maintaining model performance, then model development can begin earlier. It is simpler for a radiologist to evaluate model-generated labels for accuracy than to spend time assigning labels; the former approach thus further decreases the amount of human effort required to prepare training datasets [10]. Active learning approaches may thus yield more efficient resource use.

A limited number of studies have examined the application of physician-in-the-loop active learning frameworks for radiology AI models. These studies have included interactive segmentation tasks, such as of the pancreas and spleen on abdominal CT, hippocampus on brain MRI, and bones of the finger on hand radiograph, where physician-in-the-loop tools have significantly reduced radiologist interaction time while maintaining or improving segmentation accuracy [51,52,55], In another study, radiologists provided manual adjustments and other feedback on AI-generated annotations through an open-source RIS, resulting in improved model performance [56]. In an additional study, active learning was used to train an AI tool for disease classification (e.g., COVID-19, other pneumonias) on chest radiographs, yielding a substantial reduction in labeling effort while achieving performance comparable to fully labeled datasets [10]. Table 1 summarizes selected studies categorized according to the active learning workflow step.

Interactive segmentation and annotation tools have been developed for various modalities [55–57]. These tools have entailed different user interfaces, ranging from options to simply accept or reject the outputs of the underlying models to opportunities to provide more nuanced manual segmentation or label refinement. The specific interaction depends on the model's purpose. For example, a classification model may require accepting or rejecting a label, whereas a segmentation model may require manual refinement. Bangert et al. [10] demonstrated in several case studies that, after a certain small percentage (e.g., 10%) of a dataset is human-labeled, the remaining data can be handled through AI-generated labels with expert review, a much simpler task than manual annotation of the full dataset. An interactive segmentation method proposed by Wang et al. [58] utilized user-drawn bounding boxes for initial model prediction with optional further refinement using scribbles. That method achieved a significantly improved Dice score for segmenting certain structures on fetal MRI, with a segmentation refinement time for the user that was generally shorter than 30 seconds. Finally, Sakinis et al. utilized interactions based on mouse clicks for segmentation of the spleen and colon cancers on CT, observing that a limited number (typically 1-3) of clicks were required to produce accurate segmentation [55].

Overall, these studies highlight the potential for active learning to reduce radiologist workloads while improving model performance. Additionally, the studies highlight various interactions between radiologists and AI tools, emphasizing collaborative efforts in achieving tasks and acquiring feedback. However, challenges remain, including error analysis, testing across diverse use cases, and evaluation of feedback from radiologists on system usability and workflow impact.

Clinically meaningful use cases for active learning must be identified and explored, focusing on those yielding results that may change patient management. Additionally, active learning tools should be evaluated in dimensions including ease of use and time saved for annotation. Studies investigating active learning models for radiology-relevant tasks should also consider a typical radiology practice's available computing resources. Coordinated approaches between radiology practices and AI model developers and vendors will ultimately facilitate more informed decision-making during creation and adoption of AI solutions. Table 2 summarizes key points that radiology practices should consider before implementing active learning AI models.

Challenges, Limitations, and Risk Mitigation

The integration of active learning tools into clinical workflows faces several challenges. First, training typical AI algorithms requires significant computational resources, including graphics processing units (GPUs); subsequent deployment in clinical settings may require additional computing power. Computational burden can be alleviated by employing methods such as incremental and continual learning and by fine-tuning existing models to learn from new data [59,60]. Additional solutions for optimizing GPU usage include the saving of radiologists' modifications on separate GPUs, leveraging of neural networks on single GPUs, and hosting of AI models on privacy-compliant cloud-based storage solutions with access to online GPU resources [61].

Other considerations include promotion of collaboration between radiologists, AI scientists, and IT staff during deployment; continual quality control and evaluation of the AI tool; and increases in computational resources to decrease time in transferring data between PACS and the AI host system [62]. To meet these needs, financial resources should be procured to employ and train all participating staff in the relevant responsibilities. Additionally, radiology practices should collaborate with AI vendors to ensure that the potential AI solution's implementation is efficient and economically feasible.

Another concern relates to potential degradation of model performance if misclassified or conflicting data are included. This issue can potentially be mitigated by training on larger batches of data and testing performance on an external dataset with inclusion of quality assurance checks. Active learning should be used to increase data collection for useful samples, periodically updating a model for future deployment after regulatory approval rather than directly affecting the current system's performance. Active learning may also mitigate bias and improve fairness in training data collected for particular groups [63]. Annotation variability, such as inconsistencies between junior and senior radiologists, may introduce noise in training data that can be mitigated by consensus-based labeling involving multiple users and regulatory-aware update cycles. Although active learning maintains the physician in the loop, active learning tools developed for clinical tasks still must ensure that the tool does not compromise the physicians' control over their own work; such an aim can be sought, for example, by prioritizing the minimization of annotation efforts [64]. Furthermore, retraining models with newly labeled data may cause the model to forget its initial knowledge; continual learning techniques can help mitigate this phenomenon [65].

Additional considerations include compliance with legal standards, protection of patient privacy, and evaluation of the impact of AI on clinical decision-making [66,67]. For active-learning-enabled AI tools that require continuous updates and re-training, it is critical to follow FDA regulatory guidelines including creation of a predetermined change control plan that addresses anticipated updates to the tool along with methods to implement such changes [23]. Finally, ethical considerations including transparency with respect to algorithms' evolution, determination of the accountable entities for ensuring AI tool performance, as well as approaches for anticipating and preventing undesirable consequences (e.g., unintended model bias) [25] all require further exploration.

Future Trends and Research Directions

Future efforts in active learning include refinement of learning theory to optimize model performance and refinement of methods to generate data, fine-tune models, and incorporate tools into radiology practice. Active learning performance should be assessed across tasks (e.g., segmentation, classification, and generation) and metrics, including model performance, reproducibility, and user satisfaction. These aims can be accomplished through automated metrics, surveys, or human observer studies, applying the collected feedback to guide active learning development. Radiologists may also collaborate in curating datasets that emphasize challenging, ambiguous, and rare cases, maximizing model generalizability.

For active learning tools, performance metrics should extend beyond traditional criteria, such as the Dice score or Jaccard index [68], and instead explore more clinically relevant objectives including staging accuracy, disease detection, workflow efficiency, and overall physician workload [69–71]. Downstream clinical impact must also be evaluated.

Foundation models are large-scale multimodal models capable of adapting to various applications [72]. Emerging foundation models like the segment anything model (SAM) and its derivatives (MedSAM, GazeSAM) will better enable refinement of AI systems to different tasks based on clinician feedback, enhancing the scalability of the labeling process [73–76]. As such models' development requires large multimodal datasets, active learning strategies may also support foundation models in acquiring domain knowledge more efficiently [77]. When semi-supervised tasks incorporate model-generated annotations, re-weighting methods (for both expert- and model-generated samples) should be used to preserve model performance [78].

Integration of active learning into clinical practice will require consideration of guidelines for data collection, development, evaluation, deployment, and governance [79–82]. New AI tools must also be viewed from an implementation science perspective, whereby knowledge creators and users partner in overcoming barriers to use through four core domains: reason to use, means to use, method to use, and desire to use [83]. Effective radiologist education in the application of AI tools could help improve the reliability of radiologist-labeled data. As AI use increases, practice guidelines should be developed to address the proper use of active learning in clinical decision-making [80].

Emerging generative AI and large language models (LLMs) may also warrant incorporation into active learning systems. In radiology workflows, LLMs have the potential to be used for such tasks as processing, structured report generation, image enhancement, and image synthesis [84]–functions that may support an active learning system by providing text prompts to radiologists or by generating additional data.

Two key perspectives regarding physician-in-the-loop AI include the technical perspective that focuses on physician involvement in AI development and the clinical perspective that focuses on how physicians can effectively use AI tools in clinical practice. Advancing physician-in-the-loop AI will require collaboration and progress in both domains to ensure that AI tools are effective and demonstrate clear clinical utility.

Overall, near-term recommendations include the identification of unmet clinical needs that will benefit from the use of active learning AI models, development of user-friendly interfaces, exploration of privacy-compliant storage solutions, and education of radiologists and trainees. Long-term recommendations include the development or adaptation of existing guidelines and regulations to include active learning models, increased collaboration between radiology practices and AI vendors, and integration of active learning tools within radiology workflows to enable efficient interactions and improved outcome predictions. Figure 5 summarizes these recommendations.

Conclusion

Active learning AI focuses on the most uncertain or informative cases to avoid the need for extensive labeling and thereby reduce radiologists' labeling burden. By continuously querying experts on challenging cases, models trained via active learning evolve in real-time to facilitate AI development and improve radiology workflows. As a technique to enable interactive learning, active learning facilitates iterative improvements to AI tools and ultimately promotes closer physician-AI interactions. Active learning may also contribute to development of foundation models, which require large multimodal datasets, by improving the scalability of the labeling process. However, challenges remain, including limited integration into commercial software. Needs exist to evaluate active learning tools in terms of reproducibility, user satisfaction, and ease of integration to improve scalability. Ethical considerations, system performance, integration processes, and end-user education must also be more deeply explored before implementing active learning in clinical workflows. Despite these issues needing to be further addressed, active learning currently represents a promising frontier for encouraging physician-in-the-loop radiology AI workflows.

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Table 1 – Published studies applying active learning for radiology artificial intelligence tools

First Author [Ref]	**Active Learning Use Case**	**Workflow Steps**
Bangert [10]	Classification of COVID-19 on chest radiograph using partial labels	Labeling and annotation
Sakinis [55]	Interactive CT segmentation using mouse clicks	Postprocessing and segmentation
Purkayastha [56]	Radiologist feedback via radiology information system integration	Feedback and model updating
Nath [52]	Segmentation with uncertain case prioritization	Model training and retraining

Table 2 –Domains and actions that radiology practices should investigate before introducing an active learning artificial intelligence (AI) model into clinical practice.

Domain	**Actions**
Clinical relevance	Identify specific clinical objectives. Evaluate if the AI solution fulfills clinical objectives.
Model performance	Validate model performance and confirm reliability and consistency of AI predictions.
Integration capability	Check system compatibility with existing infrastructures, including PACS and radiology information system.
Workflow efficiency	Assess impact of AI tool on clinical workflow efficiency. Optimize ease of interaction between radiologists and the AI tool.
Data security	Confirm compliance with regulations, ethical standards, and privacy laws.
Training and support	Provide ongoing training and resources for radiologists and technical staff.
Continuous improvement	Establish structured feedback mechanisms, regular updates, and maintenance plans.

Figure Legends

Fig. 1 – Active learning sampling strategies. Membership query synthesis generates most informative data for annotation by so-called oracle. Stream-based selective sampling processes dataset as stream, selecting individual samples sequentially. Pool-based sampling evaluates large pool of data to identify and select most informative samples. (Icons copyright UXWing; used with permission)

Fig. 2 - Representative steps in typical radiology workflow: (1) Ordering physician submits imaging request. (2) Patient is registered in RIS. (3) Imaging examination is performed. (4) Acquired images are reviewed and transmitted to PACS. (5) Postprocessing is performed. (6) Images are transmitted to radiology workstation and/or PACS. (7) Radiologist reviews images and generates report. (8) Report is transmitted to RIS. (9) Ordering physician reviews report. (10) Imaging findings are discussed at multidisciplinary conference. RIS: radiology information system. (Icons copyright UXWing; used with permission)

Fig. 3 - Integration of active learning cycle into radiology workflow. (1) Active learning cycle is embedded within step 7 of typical radiology workflow shown in Figure 2. (2) While radiologists receive patient images and perform clinical duties (e.g., report generation), they are provided with the option to contribute interactive feedback to AI model (e.g., accepting, rejecting, or modifying provided labels). (3) Newly provided labels are added to model's training pool. (4) Model is periodically updated based on process overseen by professionals including AI scientists, quality assurance staff, and information technology (IT) support staff. (5) When model identifies most uncertain cases, radiologists receives prompt from model to review or provide labels for such cases. AI = artificial intelligence. (Icons copyright UXWing; used with permission)

Fig. 4 – Use of gaze-tracking tool within software program (3D Slicer; Version 5.6.2) to segment PET/CT image. Software tracks radiologist's eye movements, applying this information to delineate bounding boxes and segment areas of interest.

Fig. 5 - Summary of recommendations for design, development, implementation, and integration of active learning into clinical radiology AI workflows. IT = information technology. AI = artificial intelligence. (Icons copyright UXWing; used with permission)