Moving the Needle Forward: Interventional Oncology in the Era of Clinical Artificial Intelligence

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ABSTRACT

The future of interventional oncology (IO) is closely linked with its past and present as a field that combines cutting-edge technology with advances in minimally invasive techniques and knowledge of disease processes. In the era of personalized medicine, current and emerging advances in artificial intelligence (AI) offer tools that may enhance many aspects of IO — from screening to treatment and follow-up, to patient education and provider training. In conjunction with advances in augmented reality (AR) and robotics, these applications may provide increased precision, efficiency, and personalization in care, allowing practitioners to optimize clinical practice and reduce fatigue from heavy workloads and administrative responsibilities.

Through delegation of repetitive and/or time-consuming tasks, AI tools allow physicians to prioritize duties and skills that require human expertise. However, many of the AI technologies being implemented and described in the literature exist in isolation and in various states of development, making it difficult to appreciate the full impact of clinical AI in IO in the near future, when the myriad applications have been sufficiently validated and are operating in concert to influence cancer management. The present review surveys the clinical AI ecosystem as it pertains to interventional oncology, from initial screening to remission, with particular emphasis on expected benefits to clinical workflow and the overall patient experience.

Keywords: Artificial Intelligence, Interventional Oncology, Deep Learning, Deep Learning Reconstruction, Radiomics, Augmented Reality, Robotics, Generative Adversarial Networks

INTRODUCTION

Since the introduction of percutaneous tumor embolization and ablation in the late 20th century, interventional radiologists have played an integral role in the management of solid organ cancers, with their unique vantage point at the intersection of diagnostic imaging and clinical oncology allowing for

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targeted locoregional therapy. The precise navigation of needles and catheters into tumors within the patient effectively externalizes and expands the procedural field, relying on real-time integration of direct sensorimotor and digital imaging data to reduce morbidity and mortality compared to surgical resection. However, demand for minimally invasive options for a growing number of oncologic indications is taxing the ability of interventional oncologists to meet clinical needs, especially given the longitudinal, multidisciplinary nature of cancer care and the extensive preparation required for interventional oncology (IO) procedures.

In light of this and other challenges stemming from the inherent complexity of neoplastic processes, the growth of interventional oncology in the 21st century will invariably be driven in large part by the enhanced processing and analytical capabilities of AI. The current and potential clinical applications of *deep learning* – i.e., the operation of multilayered neural networks in a manner inspired by human cognition to extract and learn from large datasets with minimal human intervention – are expansive and largely limited by the resources and regulations required for their training and use. Many of these tools are actively being developed and validated, often with limited applications and patient populations, but are already demonstrating considerable promise in key domains including screening, diagnosis, procedural planning, and prognostication.

With its reliance on advanced technologies for the interpretation and utilization of multimodal imaging data to facilitate diagnostic and procedural precision, IO is particularly well-primed for an AI-facilitated transformation of clinical workflow and best practices **(Table 1)**. This review highlights recent developments of AI in IO as presented in the current literature, with brief mention of concomitant advances in *augmented reality* (AR) and robotics as pertinent to the AI-IO ecosystem. A literature search was conducted using PubMed with the following terms: “artificial intelligence,” “machine learning,” “deep learning,” or “neural network,” and “interventional oncology,” “oncology,” “radiology,” or “interventional radiology,” with a particular focus on review articles and

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clinical studies published between 2019 and 2025. Additional articles were identified through manual review of relevant citations from the initial articles.

Table 1. Clinical Applications of AI in Various Domains of Interventional Oncology

Clinical Domain	Subdomain	Advantages Conferred by AI	Clinical Readiness
Initial Encounter	**AI Clinical Tools**	AI scribing, assisted clinical decision-making	In clinical use
	AI-EMR Integration	Synchronization of clinical data and AI applications; readily available training datasets; alerts and flags for important clinical data and workflows	In clinical use
Screening	**Opportunistic Screening**	Passive review of basic demographic and clinical data for suggested follow-up options	Proof of concept
	Targeted Screening	Comprehensive synthesis of all EMR data for tailored screening recommendations; automated scheduling and referrals	Proof of concept
Diagnosis	**Personalized Imaging Acquisition**	Improved imaging quality, efficiency, and diagnostic utility per scan; modifications of protocols as needed tailoring to diagnosis	FDA-approved for clinical use
	Deep Learning Reconstruction	Contrast/radiation dose reduction, artifact reduction, shorter acquisition time, enhanced image quality	FDA-approved for clinical use
	Lesion Detection and Characterization	Enhanced diagnostic radiologist sensitivity and productivity; better adherence to guidelines	In clinical use
	Digital Histopathology	Enhanced pathologist sensitivity and productivity	In clinical use
Prognostication	**Radiomics and AI-RADS**	Decreased variability and subjectivity in lesion characterization and reporting	Preclinical trials
	AI-opsy vs. Biopsy	Informed patient decision-making based on personal degree of comfort with surveillance vs. invasive tissue sampling	Proof of concept
	Disease Course Simulation	Improved patient and provider understanding of necessity and urgency of treatment	Proof of concept
	Pathology, Pathomics, Genomics, and other "-omics"	Enhanced understanding of disease biology; applications in precision medicine	Preclinical trials
Treatment	**Targeted Treatment Options**	Automated analyses of candidacy for interventional/surgical options and clinical trials	Proof of concept
	Outcome Prediction	Improved patient selection and anticipation of periprocedural morbidity; improved expectation management for treatment outcomes	Preclinical trials
	Pre-Procedural Planning	More efficient and accurate segmentation of treatment zones, lesions, and organs	FDA-approved for clinical use
Procedural Optimization	**Intraprocedural Guidance**	Increased precision and safety of needle/catheter manipulation	FDA-approved for clinical use
	Augmented Reality	Improved procedural ergonomics, shorter procedure duration	In clinical use
	Interventional Robotics	Reduced procedural fatigue and human error; potential for expanded reach via tele-IR suites	In limited clinical use; in clinical trials
	Peri-Procedural Monitoring	Detection of subtle/early signs of procedural complications	In clinical use
	Peri-Procedural Pain Management	Decreased variability and subjectivity in pain control, reduced morbidity from anesthetic/analgesic regimen	Proof of concept
Surveillance	**Personalized Follow-Up**	Customizable schedule adjusted based on clinical, lab, and imaging parameters	Proof of concept
	Remote Patient Monitoring	Detection of subtle/early signs of disease recurrence or treatment-related morbidity	In clinical use
	Residual Disease and Recurrence	Increased sensitivity for detection of residual/recurrent disease vs. post-treatment changes	Preclinical trials
Multidisciplinary Engagement	**Centralized Cancer Synopsis**	Unified understanding of a patient's condition and treatment course based on input from all providers involved in care	Proof of concept
	Tumor Board Facilitation	Improved consistency and efficiency, decreased human error in the review and summary of pertinent EMR data	Proof of concept
	Research (Basic, Translational, Public Health)	Novel insights on disease biology, drug development, and population-level trends from AI-EMR data	Preclinical and clinical trials
Education	**Patient Education**	Auto-generated, personalized resources on diagnosis and treatment available 24/7	In clinical use
	Medical Education	Simulated images to improve diagnostic and procedural decision-making skills	Preclinical trials
Workflow Optimization	**Report Generation**	Improved consistency, efficiency, productivity; standardized templates with reduced human error and subjectivity	In clinical use
	Administrative Tasks	AI-assisted or automated scheduling, referrals, patient communication, billing/coding	In clinical use

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We follow the clinical journey of a patient in a hypothetical but plausible near future, when the most promising AI technologies being reported in the current literature have been vetted, approved, and implemented in active clinical use within the field of interventional oncology.

OPPORTUNISTIC SCREENING

The patient initially presents to their primary care provider, who upon conducting and documenting a clinical exam with an AI scribe integrated into the electronic medical record (EMR), receives an automated alert that the patient qualifies for cancer screening. While the clinician opens the visit by addressing the patient's chief complaint, other EMR-integrated AI applications conduct opportunistic screening in the background.

The data-mining and multitasking capabilities of machine learning algorithms in the EMR allow for consistent and expedient synthesis of a given patient's medical record for real-time risk stratification — even for disease processes that have no apparent connection to the reasons the patient presented in the first place.[1,2] Park et al. used data from a large cohort of 425,148 patients to demonstrate the feasibility of personalized preventative healthcare to predict risk of mortality and five major chronic diseases based on variables categorized within demographics, lifestyle, family history, and wearable device data, with or without the inclusion of laboratory data.[3] Predictive analytics such as these can help reduce healthcare costs and extraneous diagnostic tests while improving clinical efficiency and patient outcomes.[4-6] From a patient perspective, this would mean more actionable information for fewer encounters and fewer procedures.

By the end of the visit, the clinician and patient are provided with recommendations for additional labs and imaging, and together they select the ones with the highest expected diagnostic yield based on prognostic models that are regularly updated as the convolutional neural networks (CNNs) learn from the results of the entire patient population. The patient undergoes the

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appropriate imaging studies, with AI facilitating significant reductions in acquisition time, radiation exposure, and intravenous contrast.

DIAGNOSIS

While most current applications of AI in diagnostic radiology involve post-acquisition analysis of imaging data, AI is also expected to transform traditional reconstruction methods that employ filtered back projection (FBP) or iterative reconstruction (IR) algorithms. *Deep learning reconstruction* (DLR) is the application of neural networks trained on imaging data to decrease acquisition time and/or radiation exposure without significant loss of the spatial and temporal resolution required to visualize and characterize findings.[7] DLR algorithms can be applied directly to the sinogram data for reconstruction without FBP or IR, or applied indirectly to optimize sinogram and/or reconstructed imaging data.[8]

Reported benefits of DLR include shorter scan acquisition times, improved signal-to-noise and contrast-to-noise ratios, artifact reduction, and enhanced visibility of lesions and anatomic detail (**Table 2**).[7,9] Several groups testing AI-enhanced imaging protocols have reported 36-70% reduction in radiation exposure for pediatric computed tomography (CT) without significant loss of diagnostic information, while other groups have achieved 50-90% reduction in intravenous contrast dose for CT or magnetic resonance imaging (MRI).[7,10,11] Similar studies exploring optimization of positron emission tomography/CT (PET/CT) protocols could result in reduced doses of radiotracers and/or radiation required to identify lesions and characterize their functional status.[12]

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Table 2. Applications of Deep Learning Reconstruction in Diagnostic and Interventional Radiology

	Phase of DLR	Advantages conferred by Deep Learning Reconstruction	Clinical Readiness
Diagnostic Radiology	Pre-Acquisition	Personalized optimization of imaging parameters based on BSA, GFR, prior imaging, etc.	FDA-approved for clinical use, in clinical trials
	During Acquisition	Reduced acquisition time, contrast and/or radiotracer dose, radiation exposure	FDA-approved for clinical use, in clinical trials
		Dynamic imaging data to evaluate cardiac function and lesional perfusion patterns	Proof of concept
		Direct DLR: algorithms applied to sinogram without the need for FBP or IR	FDA-approved for clinical use, in clinical trials
		Indirect DLR: algorithms applied to sinogram and/or FBP/IR-reconstructed images	FDA-approved for clinical use, in clinical trials
	Post-Acquisition	Reduction of artifacts related to susceptibility, beam hardening, and/or motion	FDA-approved for clinical use
		Improved SNR and CNR for lesion visibility and anatomic detail	FDA-approved for clinical use
Interventional Radiology	Pre-Procedural	Multimodal fused imaging overlays for needle and catheter guidance	In clinical trials
	Intra-Procedural	Digital angiography without the need for mask layers required for DSA	In preclinical trials
		Auto-collimation during fluoroscopic interventions	In preclinical trials
		Reduced acquisition time, radiation exposure, and artifacts in CT-guided procedures	FDA-approved for clinical use
		Improved SNR of small vessels, CNR of lesions, and visualization of feeder arteries	In clinical use
	Post-Procedural	Prediction of treatment outcomes from intraprocedural imaging	In preclinical trials

Abbreviations: BSA: body surface area; CNR: contrast-to-noise ratio; DLR: deep learning reconstruction; DSA: digital subtraction angiography; FBP: filtered back projection; GFR: glomerular filtration rate; IR: iterative reconstruction; SNR: signal-to-noise ratio

Before image acquisition, DL algorithms incorporated into scanners and integrated with EMR data can optimize imaging parameters.[14] Automated analysis of individual patient factors such as body mass index, renal function, prior imaging, and clinical indication may allow for highly personalized imaging protocols that maximize diagnostic utility and image quality while mitigating potential harm to the patient.[7]

PROGNOSTICATION

While the diagnostic radiologist conducts a visual analysis of the AI-enhanced images, other AI algorithms are applied in parallel to the raw imaging data to gather additional information

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regarding staging and prognostication. These algorithms analyze static and dynamic features of images during acquisition to generate a detailed synopsis of the tissue composition, vascularity, and expected biologic behavior of lesions based on imperceptible patterns of attenuation and enhancement. This synopsis is incorporated into an AI-generated imaging report that is reviewed, edited, and approved by the radiologist.

Broadly defined, *radiomics* is the extraction, pattern recognition, and quantification of imaging features not accessible to visual analysis for the prediction of diagnosis and treatment outcomes.[13,14] Deep learning models are being trained to not only identify lesions and features suspicious for malignancy across all imaging modalities and organ systems, but also to provide differential diagnoses and to stage and subtype cancers based on radiologic markers, with or without the incorporation of clinical and genomic data (**Table 3**).[15,16] Once validated for clinical use, such tools may reduce the need for tissue biopsies for histopathologic characterization and facilitate highly personalized management strategies.[18]

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Table 3. Select Applications of Radiomics in Interventional Oncology

Organ	Scan Type	Brief Description	Validation Status	Performance Benchmarks	Author and Year
Brain and Spinal Cord	**MRI**	Delineate low-grade vs. high-grade gliomas	Retrospective	AUC 0.93 for discriminating low vs. high grade, AUC 0.89 for classifying grades 2-4	Pitarch et al 2023
		Predict recurrence of glioma after treatment	Retrospective/prospective	C-index 0.76 in training set, 0.69 in the validation set	Liu et al 2022
Pulmonary	**CT**	Delineate pulmonary adenocarcinoma vs. SCC	Retrospective/prospective	AUC 0.88, accuracy 83%	Selvam et al 2024
		Identify and predict EGFR mutational status of pulmonary nodules to aid patient selection for targeted therapy	Retrospective	AUC 0.59-0.91	Batra et al 2024
		Predict pneumothorax and length of stay after transthoracic biopsy	Retrospective	AUC 0.91 for predicting iatrogenic pneumothorax	Sinha et al 2020
		Simulate microwave ablation zone deformation from heat-sink effect and organ margins	Retrospective	Median DSC 0.62 (compared to 0.56 for vendor models)	Keshavamurthy et al 2024
		Predict LTP after radiofrequency ablation of CRC metastases	Retrospective	AUC 0.72, accuracy 0.79	Crombe et al 2023
	XR	Detect pulmonary nodules on chest radiographs	Prospective clinical trial	Sensitivity 75-100%, specificity 80-100%, accuracy 81-100%	Albadry et al 2022
Adrenal	**CT**	Predict local tumor progression and overall survival after thermal ablation of adrenal metastases	Retrospective	AUC 0.93 for predicting LTP	Daye et al 2019
Renal	**CT**	Delineate renal clear cell carcinoma vs. angiomyolipoma	Retrospective/prospective	AUC 0.98 in training set, 0.92 in test set	Ma et al 2021
GI	**MRI**	Predict complete pathologic response in CRC after chemoradiotherapy	Retrospective	AUC 0.79	Delli Pizzi et al 2021
Hepatobiliary	**CT**	Predict TR, survival outcomes, extrahepatic metastasis, vascular invasion, and recurrence following transarterial chemoembolization (TACE), Y90, and/or ablation from pre-treatment CT	In clinical/preclinical trials	**TACE**: AUC 0.80-0.99 for TR and 0.70-0.96 for OS; C-indexes 0.88 for TR and 0.80 for OS **Y90**: pooled sensitivity 0.84 and specificity 0.87 for TR **Ablation**: AUC 0.83-0.98 for local tumor control	Hsieh et al 2023, Mirza-Aghazadeh-Attar et al 2024, Zhang et al 2024, Matsui et al 2025
	CT, MRI	Predict FLR% and KGR for portal vein embolization in patients with CRC liver metastases	Multicenter retrospective	Accuracy 86% and AUC 0.91 for predicting sufficient FLR% in internal test set, accuracy 80% and AUC 0.88 in external test set	Kuhn et al 2025
	MRI	Predict HCC recurrence following liver transplantation	Internal/external	AUC 0.99 for internal validation cohort, AUC 0.90 for external validation cohort	Schindler et al 2025
	SPECT/CT	Simulate post-treatment Y90 distribution and absorbed dose	Retrospective	Average absorbed dose difference of 5.4% and 0.44% for the tumor and liver areas, respectively, between real and predicted PET/CT scans	Plachouris et al 2021
Genitourinary and Gynecologic	**US**	Assess malignant risk in ovarian tumors vs. O-RADS	Prospective clinical trial	AUC 0.96-0.99 for training set, AUC 0.87-0.93 for test set	Du et al 2024
	CT	Delineate benign vs. malignant testicular masses, lymphoma vs. non-lymphoma	Retrospective	AUC 0.95 for benign vs. malignant testicular masses	Hu et al 2024
	MRI	Predict muscle-invasive bladder cancer	Internal/external	Pooled sensitivity 0.81-0.84, specificity 0.79-0.87, AUC 0.85-0.92	He et al 2024
		Improve patient selection for prostate biopsy vs. PI-RADS	Retrospective	Spared 49% of biopsies (compared to 37% spared with PI-RADS $\geq$ 4 cut-off) while maintaining 94% NPV	Schrader et al 2024
		Predict bone metastases from primary prostate cancer	Randomized controlled trial	AUC 0.93	Zhang et al 2024
	PET/CT	Delineate cervical adenocarcinoma vs. SCC	Internal/external	Accuracy 0.92, AUC 0.85 for internal validation cohort; AUC 0.73 for external validation cohort	Liu et al 2024
Breast	**MG**	Classify breast tissue density	Internal/external	AUC 0.86-0.95	Chen et al 2025
	MG	Detect breast cancer, classify ductal carcinoma in situ (DCIS) vs. invasive carcinomas vs. benign masses	Internal/external	AUC 0.73-0.88 for detecting malignancy, AUC 0.76 for classifying DCIS, 0.85 for invasive carcinomas, 0.82 for benign masses	Barros et al 2023
	MG+US	Delineate triple negative breast cancer from other molecular subtypes	Retrospective	AUC 0.97, accuracy 0.95, sensitivity 0.91, specificity 0.94	Ma et al 2022
	US	Predict axillary lymph node metastasis in early breast cancer	Retrospective	Accuracy 0.93 (compared to radiologist 0.85), AUC 0.93	Oshino et al 2025
Bone	**XR**	Detect and classify benign vs. malignant primary bone tumors; delineate osteosarcoma vs. Ewing sarcoma	Internal/external	AUC 0.92 for malignant vs. non-malignant, accuracy 72% for benign vs. intermediate vs. malignant	He et al 2020, Liu et al 2022; Xiang et al 2025
	MR	Detect and segment osteosarcoma vs. Ewing sarcoma	Retrospective	DSCs 0.71-0.96 with 18% reduction in mean time for semiautomatic vs. manual segmentation	Dionisio et al 2020
Soft Tissue	**US,MRI**	Diagnose malignant soft tissue tumors	Retrospective/prospective	AUC 0.89 retrospective dataset, 0.85 prospective dataset	Xie et al 2024
	MRI	Differentiate benign vs. malignant sacral tumors	Retrospective	AUC 0.77, accuracy 0.71	Yin et al 2019
Whole Body	**PET/CT**	Auto-segmentation and prognosis of several cancer types	Retrospective	Median TP rates of 0.75-0.87 and median DSCs from 0.73-0.83 for tumor segmentation; accuracy 0.72, AUC 0.72 for prediction of complete TR in breast cancer	Leung et al 2024

Abbreviations: AUC: area under curve, CRC: colorectal cancer, DSC: Dice similarity coefficient, EGFR: epidermal growth factor receptor, FLR%: future liver remnant, KGR: kinetic growth rate, LTP: local tumor progression, NPV: negative predictive value, O-RADS: Ovarian-Adnexal Reporting and Data System, OS: overall survival, PI-RADS: Prostate Imaging Reporting and Data System, RCC: renal cell carcinoma, SCC: squamous cell carcinoma, TR: tumor response

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The various reporting and data system (RADS) criteria currently employed by diagnostic radiologists to predict the likelihood of malignancy may become obsolete as radiomics-based algorithms evaluate lesions with greater precision, speed, and consistency than their human counterparts. Once established and validated, automated "AI-RADS" criteria may allow radiologists to triage imaging studies and prioritize those that are complex or equivocal. Radiomic models may further enhance diagnostic precision and certainty by correlating input from multiple imaging modalities to extract more radiopathologic and functional data than a single modality alone.[14,19]

Through *generative adversarial networks* (GANs) that alternately train discriminator and generator algorithms on real and AI-generated imaging data, radiomic tools can produce predictive images of expected disease progression based on the radiopathologic characteristics of the lesions and features of the patient's individual anatomy.[20,21] For example, AI models have been introduced to predict bone metastases in prostate cancer based on MRI, axillary lymph node metastases in early breast cancer based on contrast-enhanced US, and future liver remnant following portal vein embolization for colorectal cancer liver metastases.[9,22] The enhanced predictive power of radiomics may one day provide more than a snapshot of the present disease state, yielding instead a customized imaging portfolio of the predicted outcomes of various treatment options (**Table 3**).[21,23]

BIOPSY VS. RADIOMICS-BASED VIRTUAL BIOPSY

The patient, who was automatically referred for an oncology clinic visit based on the new laboratory and imaging results, receives a radiomics-based virtual biopsy ("AI-opsy") report that combines all the pertinent data into a succinct, plain language summary of the likely diagnosis, differential diagnoses, and likelihood of concordance between the imaging features and expected pathology findings for a percutaneous biopsy. If the patient would like to pursue clinical surveillance instead of biopsy, they are provided with a customized schedule for laboratory and imaging follow-up and appropriate educational *materials to facilitate informed decision-making.*

To address low-complexity concerns and minimize the extent of potentially erroneous information absorbed by the newly diagnosed cancer patient in their quest for answers, interactive clinical AI interfaces can be incorporated into patient portals to allow for 24/7 access to medically sound information without jeopardizing the work-life balance for human clinicians.[5,24] A recent meta-analysis of 57 studies that evaluated responses generated by ChatGPT-4 to medical inquiries reports a median value of 80.35% for accuracy of responses, with significant improvements expected for *large language models* (LLMs) trained specifically on high-quality evidence-based datasets and population-level EMR data.[14,17]

If the patient proceeds with a biopsy, the interventionalist may use AI tools to aid various aspects of biopsy planning, such as plotting the optimal approach and predicting complication risks based on the specific imaging modality chosen for guidance.

Various groups are developing and trialing deep learning models for improved needle tip localization for imaging-guided percutaneous interventions, some with multimodal, real-time overlays such as pre-procedural CT for intraprocedural 2D US.[25-32] Whether such DL tools process images during acquisition to generate and display auto-annotated maps or exist within the Picture Archiving and Communication System (PACS) interface as tools, the interventionalist can offload some of the cognitive burden of planning and executing a safe and successful biopsy.

AI NAVIGATION AND ROBOTIC PLATFORMS

Having reviewed and approved the AI-assisted plan for the biopsy, the interventionalist feels comfortable offering the patient the option of a remote biopsy at a tele-interventional suite closer to their home. Depending on the patient's preference regarding the degree of procedural automation, the interventionalist may either oversee an independently operating biopsy robot or steer the needle with robotic assistance from a remote console.

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Robotic platforms in various stages of development and deployment show promise in aiding both vascular and non-vascular interventions.[17,19] As these platforms continue to improve, patients may one day have the option to book simple procedures at a nearby "tele-interventional" suite, with the interventionalist performing the procedure remotely with assistance from on-site nurses and technologists. The small but increasing number of remote procedures successfully performed since the first telerobotic percutaneous nephrostomy tube placement in 2001 alludes to a future in which interventionalists can supervise several suites at once across a wider geographic range, while reducing procedural radiation exposure and physical fatigue associated with protective lead garments.[79] Beyond the significant costs, medicolegal considerations, and infrastructural barriers, the potential of tele-IR is contingent on the nature of the interface between human operators and robots, the balance of clinical gestalt and situational awareness with enhanced precision and dexterity.

The incorporation of deep learning models into the development and training of interventional robotic platforms will allow for greater efficiency, precision, and autonomy in robot-assisted percutaneous interventions as engineers attempt to close the considerable *Sim2Real* ("simulation to reality") gap by systematically identifying and minimizing discrepancies between simulated training environments and real-world applications.[2,24] Through rigorous pre-training in simulated environments involving multiple permutations of intraprocedural conditions (*domain randomization*), interventional robots can receive positively or negatively weighted feedback to aid in optimal decision-making during trial-and-error (*reinforcement learning*).[24]

Subsequent incorporation of real patient imaging data in training datasets, with or without GAN-facilitated "translation" of real-world data into simulated formats, allows for fine-tuning of robotic parameters to facilitate seamless Sim2Real transfer of knowledge and skills into actual practice.[19,30] Robotic adaptation to clinical practice can be further optimized

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by additional strategies such as *feature alignment* (mapping of simulated and real-world data onto a shared representational space) and *policy stitching* (combining separately trained modular “robot” and “task” policies through aligned features).[77]

STAGING AND TREATMENT PROGNOSTICATION

The biopsy samples are prepared and interpreted with AI assistance for molecular and genomic profiling, allowing for increased efficacy and precision in management strategies based on therapeutic susceptibilities, predicted outcomes, and prognosis. A succinct profile of the patient and disease, generated through EMR data-mining models similar to those used during the initial visit, is sent along with referrals to the appropriate consultant services for multidisciplinary tumor board discussion.

Deep learning models trained on whole-slide histopathologic images allow the automatic detection and quantification of specific diagnostic and prognostic features across many cancer types with accuracy comparable to that of general pathologists.[2,5,20,33] While the application of AI principles to drug discovery and basic biomedical and translational research is beyond the scope of the current review, deep learning analytics have also provided insights into the molecular status of tumors based on pathologic data, identifying the likely genes affected by mutations, predicting the RNA transcriptomic profiles, and quantifying the expression of tumor marker proteins.[2,14,20,33,34]

Such comprehensive understanding of the biologic behaviors of tumors as captured on whole-slide images will improve precision medicine as targeted immunochemotherapy regimens become standard in cancer management.[20] Similar advances in deep learning algorithms have been applied to imaging data, with the combined synthesis of histopathologic, radiologic, and clinical data yielding highly accurate information on diagnosis, prognosis, and outcome prediction for clinical decision making.[15,21,23,33]

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MULTIDISCIPLINARY ENGAGEMENT

Despite the often complex clinical histories of many cancer patients, LLMs such as ChatGPT have demonstrated promise in generating patient profiles that include a clinical summary, recommendations, and explanations that were strongly agreeable to two expert reviewers.[35] With training datasets composed entirely of up-to-date medical literature and population-level EMR data, dedicated clinical LLMs and hybrid *vision-language models* (VLMs) could someday create highly personalized patient summaries on demand, complete with annotated images, in a mere fraction of the time required by human reviewers.[2,36] The direct integration of such tools into the EMR and PACS systems would facilitate the creation of a centralized cancer synopsis within the patient's chart, allowing consultant providers to delve into the source data as needed to fine-tune and ultimately approve their specific AI-proposed roles within the multidisciplinary management of a given patient.

Based on the tumor board discussion and predicted disease course, the oncologist recommends locoregional therapy with systemic immunochemotherapy.

PROCEDURAL PLANNING

If ablation or embolization is indicated, AI tools are available to the interventionalist for procedural planning, primarily in the form of organ/tumor segmentation and prediction of treatment zones based on parameters such as probe/catheter position, adjacent and tumor-feeding vessels, and lesion morphology.

Several groups have developed algorithms for automatic segmentation of lesions, ablation zones, and whole organs for liver, lung, and prostate tumors before and after radiofrequency ablation (RFA), microwave ablation (MWA), or cryoablation, based on data from a wide range of pre- and intraprocedural imaging modalities.[23,37-40] Some of these algorithms can simulate deformation by irregular lesion margins and heat-sink and cold-sink effects from adjacent vessels in treatment zone prediction, outperforming predictive models based on vendor data obtained from *ex vivo* animal experiments.[41,42]

For pre-procedural planning of transarterial chemo- and radioembolization (TACE/Y90), AI can assist in calculating absorbed doses, characterizing vascular anatomy, and triaging responders and non-responders.[43-45] Various CNN and GAN models have successfully predicted short- and long-term outcomes for TACE/Y90 using radiologic and radiomic features of pre-procedural imaging, often in combination with clinical, laboratory, and demographic data.[21-23,45-48] As the field of radiomics continues to expand, treatment-zone prediction will likely incorporate elements of radiopathology such as tissue composition, perfusion patterns, and novel hepatic biomarkers for more precise targeting.[13,15] Concomitant advances in intratumoral immunotherapy and procedural navigation will further improve the overall patient experience by reducing the likelihood of non-target effects and expanding the feasibility and efficacy of minimally invasive locoregional interventions over surgical options.[49-51]

INTRAPROCEDURAL IMAGING RECONSTRUCTION AND GUIDANCE

During the procedure, the interventionalist will have access to AI-generated imaging overlays from pre-procedural cross-sectional imaging to facilitate 2D US needle guidance, robotic steering capabilities, and reductions in both radiation and contrast doses through deep learning reconstruction (**Table 2**).[17,21,31,52,53] Several AI platforms have also been trained to reduce imaging artifacts related to patient motion, cardiorespiratory motion, and beam hardening from instrumentation, all of which improve targeting precision.[31,43]

For renal cryoablation specifically, DLR and GAN models have been introduced to reduce the dose-length product (DLP), reduce streak artifact from probes, and generate virtual multi-phasic contrast-enhanced images.[41,42] Another algorithm has been developed for auto-collimation during fluoroscopy-guided interventional procedures that can be set to an individual operator's preferences to reduce radiation exposure and allow the user to visualize the region of interest in

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real time without interrupting the procedure to manually change the collimation settings.[18,56]

A few groups have used GAN models to generate angiographic images without the need for subtraction masks, thus eliminating misregistration while producing images that are visually similar to or better than masked digital subtraction angiography (DSA) images of cerebral, hepatic, and splenic arteries.[23,52-55] Similar comparisons of DLR to hybrid iterative reconstructive algorithms of CT hepatic arteriography (CTHA) images during TACE of hepatic tumors demonstrated significant improvements in the signal-to-noise ratio of small hepatic arteries, contrast-to-noise ratio of tumors, and feeder artery visualization.[57]

Such advances in intra-procedural guidance and image reconstruction will enable seamless and precise tumor targeting and enhance the patient experience by reducing complications, procedural time, and doses of radiation and intravenous contrast (**Table 2**).[49] AI has also been used to predict treatment outcomes from intraprocedural imaging, allowing for further intervention as needed during a single procedure to ensure maximal therapeutic efficacy. For example, a new model has been described for predicting early recurrence of HCC after MWA based on intraprocedural contrast-enhanced US fusion images.[58]

PERI-PROCEDURAL MONITORING AND PAIN MANAGEMENT

One important and often-overlooked consideration for patient safety during oncologic interventions is the need for procedural sedation, which provides patient comfort and reduces motion, though at the risk of numerous potential adverse effects, particularly when improperly dosed. Unfortunately, there is a great deal of guesswork involved in determining optimal dosage, with the patient's vitals and subjective reports of pain/discomfort often serving as the primary criteria for dosing decisions. To that end, AI-facilitated advances in continuous monitoring of physiologic biometrics (i.e., vital signs) may soon be incorporated into interventional suites to bring more precision and objectivity to the optimal dosing of procedural sedation

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and assist in detecting drug interactions and adverse reactions to minimize preventable patient harm.[5]

Remote patient monitoring (RPM) can be performed with dedicated devices or simple cameras such as those readily available on mobile phones or laptops, using AI algorithms to predict and monitor clinically relevant biometrics in real time.[59] While recent studies on RPM focus primarily on the benefits and applications to preventive healthcare[59,60], the incorporation of AI-integrated RPM into peri-procedural therapeutic drug monitoring could help usher in a paradigm shift from as-needed bolus dosing to something closer to automated basal micro-dosing for more even, uninterrupted sedation based on EMR data and a continuous stream of real time biofeedback.

In addition to optimizing procedural sedation, RPM has the potential to greatly reduce clutter in and around the procedural field by eliminating the need for physical biosensors (e.g., cords, leads, electrodes, probes, catheters) on the patient, with the added benefit of drastically reducing associated artifacts on intraprocedural imaging. Besides monitoring vitals, other biometrics acquired in the peri-procedural period can help predict complications and assist with clinical decision-making during and after procedures.

AUGMENTED REALITY GUIDED INTERVENTION

Beyond the generation of intraprocedural overlays on traditional image guidance modalities, AI algorithms paired with smartphones and dedicated *augmented reality* (AR) systems have shown considerable success in guiding percutaneous interventions in preclinical and clinical models.[53,61-64] Such systems rely on the same principles of fusion imaging to facilitate accurate needle placement while improving spatial awareness and reducing procedural time and radiation exposure.[18,63,64] Other notable benefits to the interventionalist include significantly improved ergonomics associated with a single line of vision (as opposed to alternating between monitors and the procedural field) and the ability to interact with real and virtual visual data simultaneously without the need for intermittent

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rescanning and planar reconstruction.[49,61]

POST-PROCEDURAL FOLLOW-UP

Following treatment, the interventionalist and patient are alerted to possible clinical outcomes based on peri-procedural images, and the patient is provided with a personalized follow-up schedule based on their lab and imaging findings. This schedule is adjusted based on additional clinical and imaging data, with AI-enhanced analytics allowing detection of subtle, early, or yet-undiscovered trends that might warrant earlier clinical assessment.

Few DL models in clinical and preclinical trials use imaging and EMR data to predict multiple medical events including in-hospital mortality, 30-day readmission, and prolonged length of stay to assist with post-procedural management.[1,48] Several meta-analyses published since 2023 have examined AI-based predictive models of patient outcomes following TACE, Y90, and/or ablation of liver tumors.[23,41,48,64] As summarized by Matsui et al, these models have demonstrated moderate to high performance in pooling radiologic and radiomic data with or without clinical data to predict complications, tumor response, local progression, and disease-free survival (**Table 3**).[41] Rather than relying on standardized follow-up schedules, the high-level awareness afforded by AI-generated forecasts of clinical status would allow patients and providers alike to feel more reassured in their shared decision-making regarding the frequency and nature of follow-up appointments.

Through RPM of vitals and other biometrics (e.g., EKG, sleep patterns, gait, facial features) enabled by AI-integrated mobile health apps and personal health devices synced to the EMR, the patient can keep the cancer care team broadly informed of their post-treatment status to ensure timely follow-up while avoiding unnecessary clinic visits.[2,5,59] By delegating certain aspects of routine post-treatment surveillance to AI, oncologists can optimize the balance between clinical vigilance and patient compliance to promote value-based, patient-centered care for each individual patient.[41,49]

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PROVIDER WORKFLOW AND WELLNESS

Even years later, with intermittent follow-up visits as needed, the patient appreciates the extent of meaningful interaction with their clinicians and the 24/7 availability of up-to-date, high-quality resources at every step of their journey. Meanwhile, the interventionalist is grateful for the opportunity to interact with and treat more patients as a result of tele-interventional suites and supervised automation of the more tedious aspects of their daily workload.

AI automation of tedious and relatively low-cognitive-effort tasks may allow interventional radiologists to redirect more of their time and efforts on tasks that are more cognitively demanding and as of yet require human expertise.[66-68] As cancer management is inherently more personalized and multidisciplinary compared to many other disease processes, interventional oncologists in particular stand to benefit greatly from assuming a more supervisory role for tasks that can be automated (e.g., lesion segmentation, report generation, billing, scheduling, and documentation).[34,49]

Several studies have demonstrated that AI tools can perform on par with or even better than experienced radiologists on low- and intermediate-complexity tasks, and – contrary to popular belief – the majority of practicing radiologists and trainees are enthusiastic about AI implementation in their practice rather than fearful of being replaced.[9,69,70] However, it is important to note the current dearth of literature on administrative burdens unique to clinical AI, such as training courses and modules, technical and medicolegal troubleshooting, and tasks related to the review/verification of AI-generated content (AIGC), the AI models themselves, and the datasets used to train the models.

MEDICAL EDUCATION AND INTERVENTIONAL TRAINING

One potential application of integrated VLM platforms that is relatively unexplored in the literature is in medical education, particularly for radiology residents who may already be utilizing them on a daily basis. In addition to resources such as existing medical

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LLMs, imaging atlases, video lectures, and illustrative cases presented by more senior radiologists, trainees may one day have the ability to toggle through auto-annotations of anatomic and pathologic features on real patient images in the same way they might draw a region of interest or measure angles.[36,49,71] Such tools could be deployed and configured in a graduated fashion that promotes competence and confidence in trainees without detracting from their developing search patterns and interpretational skills.

By coupling existing phantom and virtual reality (VR) simulators with AI models to generate different scenarios based on simulated or actual patient imaging data, interventionalists and their trainees can hone their procedural skills in a realistic but safe environment with real-time feedback.[2,17,24,53] Similarly, during preprocedural imaging review and educational case conferences, AI-generated post-procedural images could allow trainees to gain aptitude in their diagnostic and clinical decision-making skills through tangible evidence of the predicted consequences of their proposed actions and strategies.[49]

BARRIERS, LIMITATIONS, AND CONSIDERATIONS

Liability, Provider Readiness, and Patient Consent

What remains to be determined is the extent of utilization and visibility of AI tools from both the interventionalist's and patient's perspective. Will the interventionalist play an active role in the creation of AI-assisted plans and reports, or will AI operate on autopilot during acquisition, ready for later review and approval by a human supervisor? Interventionalists will need to know how to recognize and troubleshoot issues in real-time when AI tools fail, yet several studies have shown that radiologists and clinicians, in general, have limited training or knowledge on what AI is and how it works, let alone how they might assume manual control if the tools prove to be faulty.[9,17,33,70] In the event of patient harm, who is liable from a medicolegal perspective – the software engineer, the institution's IT department, the physician operator, or the patient who knowingly or

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unknowingly consented to AI-enhanced care?

While countless hospital systems and independent practices across the world have already adopted and integrated AI into their daily operations, there is a considerable lag or deficit in transparency and general patient awareness of the roles and responsibilities being delegated to AI, as well as any potential rights they have as patients to opt out of AI assistance in their care.[17,49,72] This may be difficult to achieve given the extent of interoperability and degree of automation of EMR integration required for many of the applications discussed, but “AI acceptance status” may someday be similar to code status in guiding providers on allowable uses of AI technologies within the parameters set by the patient.

Patient Privacy, Equity, and Transparency in AI Implementation

Another major obstacle is the need for well-curated, highly secure, large-scale databases for DL models to make reliable predictions in the face of narrow margins of error and high-stakes consequences in IO.[34,49,53,72] International collaborations such as The Cancer Imaging Archive and Genomic Data Commons Data Portal are a promising start, but the creation and maintenance of similar databases will require multi-institutional collaboration and stringent, robust regulatory mechanisms.[13,17,20,34] Furthermore, as humans or AI trained by humans ultimately design and modify AI algorithms, any clinical tools trained on population-level data are highly susceptible to, and often amplify, systemic biases in the data on which they are trained.[17,72,73] As such, every effort should be made toward ensuring impartiality at every step of design, training, implementation, and regulation of AI technologies.[74,75]

Several professional bodies and regulatory agencies have proposed guidelines and action plans for the responsible and ethical reporting, protocoling, implementation, and evaluation of AI technologies, including TRIPOD-AI (Transparent Reporting of a multivariable prediction model of Individual Prognosis Or Diagnosis), CLAIM (Checklist for Artificial Intelligence in Medical Imaging), and Radiomics Quality Score (RQS), SPIRIT-AI,

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CONSORT-AI, and the FDA's 2021 action plan on software as medical devices (SaMD).[5,17,49,73] However, global adoption of these endeavors has not yet been achieved despite the exponential growth of literature on AI in IO and general clinical medicine in recent years. Furthermore, there is a relative dearth of medicolegal or ethical guidelines pertaining to issues specific to the academic-industrial partnerships required for the integration of AI into hospital informatic infrastructures – particularly regarding patient privacy and data ownership and access rights.[34,72]

The "Black Box" and AI Artifacts

Like the human minds from which they are modeled, deep learning algorithms operate as "black boxes," with discrete outputs generated from inputs through internal processes that are not readily understood or even fully characterizable.[14,16] Without the appropriate safeguards, the recommendations and predictions generated within the black box are also subject to AI-specific artifacts such as hallucinations and reverse hallucinations that can erode patient and clinician trust and even lead to medical errors and patient harm (**Table 4**).[9,72] While a full exploration of AI artifacts is beyond the scope of the current review, hallucinations can be further subcategorized based on factors such as the level of computer logic on which they occur or the degree of deviation/contradiction from real-world facts, input data, or context.

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Table 4. AI Artifacts and Barriers to Successful Implementation of Clinical AI

Category	Description/Details
AI Features and Artifacts	
Black box	Inherent lack of transparency regarding inner workings of AI algorithms
Non-determinism	Inherently limited predictability and reproducibility of AIGC
Hallucinations	Positive fabrications from faulty training data, mismatched model complexity, and/or lack of context
Reverse hallucinations	Negative fabrications ("omissions") of viable output data
Model drift	Degradation in model performance due to changes in real-world input data
Model collapse	Degradation in AIGC quality due to recursive training on prior AIGC
Bias amplification	Exponential increase in biases introduced at any level of model production and usage
Barriers: Data Management	
Patient privacy	Significant amounts of PHI required for nearly all clinical AI tools
Data ownership	Little regulation on who owns, maintains, and can access data from AIGC
Economic and environmental costs	Algorithms require substantial computing power, which requires finite human and natural resources
Barriers: Human-AI Interface	
Patient and public perception	Potential erosion of trust in clinicians who either under-utilize or over-rely on AI
Human vs. artificial intelligence	Need to strike a good balance between human clinical expertise and enhanced processing power of AI
User buy-in vs. job security	Early adopters and trainers of AI – pioneers, or the first to be replaced?
Transparency in integration	Lack of guidelines on ethical academic-industrial partnerships; little ground-level awareness of high-level changes
Informed consent	Patient awareness of how and to what extent AI is being implemented in clinical use
Incorporation into existing workflows	Need to discuss and redefine hierarchies, roles, and expectations of human radiologists
Incorporation into medical education	Need for comprehensive AI-specific training and assessment of competency with clinical AI tools
Medical harm, error, and liability	Unclear assigning of liability

Abbreviations: AIGC: AI-generated content, PHI: protected health information

The Devolution of Math: Model Drift and Collapse

Another consideration is the strong potential for *model drift* from clinical relevance and predictive accuracy as the potential source data for DL algorithms becomes increasingly informed by and dependent on rapidly evolving best practices shaped by AI-assisted clinical insights.[17] *Model collapse* is a related phenomenon through which the quality and relevance of AI-generated content (AIGC) decays through recursive training of subsequent generations on datasets polluted by output data from the prior generations.[76] Compared to the original input, the resultant output of this digital inbreeding is less diverse, degraded in quality, and – in later stages of collapse – often bears little resemblance to the source data or desired output data. These phenomena are nontrivial in the realm of IO, as recursive training and

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generation of synthetic data are integral features of deep learning, particularly for GAN models used for image-based simulation of treatment outcomes.

While the literature is limited on current measures to recognize and prevent model collapse in clinical AI, general consensus converges on diverse, high-quality training datasets that adapt alongside the models through regular audits and a robust pipeline of new real-world data to dilute the increasingly homogenous pool of AIGC – a so-called "data stream" operating in real-time, maintained by AI and medicolegal experts working in tandem. The Data Provenance Initiative is one such global collaborative to ensure transparency, accreditation, and informed use of publicly available data for AI training,[78] but hospitals and health systems will invariably require their own regulatory bodies given the protected nature of the data involved.

CONCLUSION

Perhaps surprisingly, many of the pitfalls, barriers, and limitations discussed in the previous section are not new or unique to AI – much as AI itself is the computer- and data-driven expansion of existing human capabilities, the issues surrounding clinical AI in interventional oncology are simply high-level extensions of existing challenges in modern patient care. However, the added layers of complexity brought about by variably autonomous, interoperable AI, AR, and robotic platforms warrant urgent and regular discourse at all levels to ensure adherence to the four core principles of non-maleficence, beneficence, autonomy, and justice.

Successful actualization of the envisioned AI-IO ecosystem will undoubtedly occur in incremental ebbs and flows, with the pace set as much by regulatory practices, costs, and economic benefits as by the perceptions of patients and providers. As AI technologies in current use and in development continue to shape clinical practice and workflow in IO, early adopters in particular must balance optimistic enthusiasm with skeptical vigilance and the highest regard for patient safety and clinical efficacy.

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