Artificial intelligence in oncology: current landscape, challenges, and future directions

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Abstract
Artificial intelligence (AI) has rapidly become a central driver of innovation in oncology, reshaping cancer screening, diagnosis, prognostication, and treatment personalization across the care continuum. Recent advances in deep learning, multimodal data integration, and large language models are enabling more accurate tumor detection, biomarker discovery, and clinical decision support than was achievable with conventional methods. In this review, we summarize key applications of AI in cancer imaging, pathology, genomics, and treatment planning, and contrast them with traditional non-AI approaches in terms of performance, workflow impact, and current evidence. We discuss emerging roles of AI in clinical trial optimization and population-level cancer control, while highlighting persistent challenges including data quality, bias, explainability, regulation, and implementation in real-world settings. Finally, we outline future directions such as foundation models, agentic AI systems, and integration with precision and hyper-personalized oncology, emphasizing the need for rigorous validation, multidisciplinary collaboration, and ethical frameworks to safely translate these technologies into routine practice.

Keywords: artificial intelligence, oncology, cancer, deep learning, radiology, pathology, genomics, precision medicine, clinical decision-support

Introduction

Over the past decade, AI has moved from experimental proof-of-concept to a strategically important technology across healthcare, with oncology often cited as one of the most fertile application domains. Cancer care generates rich multimodal data—imaging, pathology slides, genomic profiles, longitudinal electronic health records (EHRs)—that are well suited to machine learning and deep learning methods, enabling pattern recognition far beyond human cognitive limits. In parallel, global healthcare and technology forecasts consistently list AI-driven diagnostics, precision medicine, and hyper-personalized care as top trends for 2025–2026, reflecting growing investment from health systems and industry. This convergence of data abundance, mature algorithms, and strong economic incentives is accelerating the deployment of AI across the cancer pathway, from screening programs to survivorship management.[2][3][4][5][6][7][8][1]

Most early AI work in oncology focused on narrow tasks such as breast cancer screening or classification of dermatologic lesions, but recent years have seen a shift toward integrated solutions that support end-to-end decision making. Large-scale studies now show that deep learning models can match or surpass expert radiologists in specific imaging tasks, and AI-enhanced pathology and genomics pipelines are becoming integral to research and, increasingly, to clinical workflows. At the same time, narrative reviews highlight substantial barriers: model generalizability across institutions, algorithmic bias, interpretability, and misalignment between AI outputs and clinician needs. Given this rapidly evolving landscape, an updated synthesis focused specifically on AI in oncology is timely for clinicians, researchers, and policy makers.[3][5][7][8][2]

In this review, we provide an overview of the current state of AI in cancer detection, diagnosis, prognostication, and therapy selection, with emphasis on imaging, digital pathology, and genomic applications. We then discuss AI-enabled treatment planning, clinical decision-support, and optimization of clinical trials and population-level interventions. Finally, we examine key challenges and future directions, including the emergence of foundation models, multimodal architectures, and agentic AI in oncology within the broader context of hyper-personalized medicine.[4][5][6][7][8][1][2][3]

Methods

This narrative review synthesizes recent literature and expert-level commentary on AI applications in oncology. A targeted search of high-impact reviews, policy pieces, and institutional reports from 2019–2026 was performed, with priority given to sources detailing AI across the cancer care continuum, including imaging, pathology, genomics, clinical decision-support, and clinical trials. Additional materials were identified from health-technology trend reports focusing on AI, precision medicine, and hyper-personalized care in 2025–2026. Studies were qualitatively synthesized; no formal meta-analysis was conducted given heterogeneity in AI tasks, datasets, and evaluation metrics.[5][6][7][8][1][2][3][4]

Results

AI in cancer screening and early detection

AI-driven tools have shown particular promise in population-level cancer screening, where small improvements in sensitivity and specificity translate into substantial public-health gains. Deep convolutional neural networks trained on mammography datasets have demonstrated performance comparable to or better than expert radiologists in detecting early-stage breast cancers, with reductions in both false negatives and false positives in retrospective evaluations. Similar advances are emerging in lung cancer screening with low-dose CT, where AI systems can quantify nodule characteristics, assess growth trajectories, and stratify malignancy risk more consistently than manual reading alone. In colorectal cancer, machine-learning-enhanced colonoscopy systems can highlight suspicious polyps in real time, potentially increasing adenoma detection rates and reducing interval cancers.[8][2][3][5]

Beyond organ-specific imaging, AI is being used to identify subtle phenotypic signatures across modalities that may indicate preclinical disease. Multimodal models integrating imaging, routine laboratory values, and EHR data can flag individuals at elevated risk for certain malignancies, prompting earlier diagnostic work-up. Spatial transcriptomics and digital pathology tools are beginning to detect microenvironmental changes that precede morphologic evidence of invasive cancer, which could eventually support ultra-early detection or risk-adapted screening intervals. These developments align with broader healthcare trends emphasizing predictive and preventive care, moving away from episodic "sick-care" toward proactive healthspan optimization.[9][6][7][3][4][5][8]

AI in radiology and digital pathology

Radiology and pathology have emerged as flagship domains for AI in oncology because of their image-centric workflows and the availability of large digital datasets. In diagnostic radiology, AI systems now assist with lesion detection, segmentation, and characterization across tumor types, providing quantitative metrics such as volume, radiomic signatures, and treatment response indices that were previously time-consuming to derive manually. This quantitative imaging—augmented by deep learning—supports more precise staging, response assessment, and longitudinal monitoring in solid tumors. Meanwhile, AI-enhanced workflow tools triage critical findings, prioritize worklists, and automate report generation, which may mitigate radiologist workload and burnout in high-volume oncology centers.[6][2][3][5][8]

In digital pathology, whole-slide imaging combined with deep learning is unlocking insights that extend beyond traditional histologic grading. Models can detect micrometastases, quantify tumor–immune cell interactions, and infer molecular alterations such as microsatellite instability or specific driver mutations directly from hematoxylin and eosin (H&E) slides. This capability can reduce reliance on costly ancillary tests in some contexts and accelerate the identification of candidates for immunotherapy or targeted agents. Emerging multimodal systems fuse radiologic, pathologic, and genomic data to classify tumor subtypes and predict treatment response, moving toward a more integrated and nuanced understanding of each malignancy.[7][3][5][8]

AI in genomics, biomarkers, and precision oncology

The maturation of high-throughput sequencing and molecular profiling has catalyzed precision oncology, and AI is increasingly central to making sense of the resulting high-dimensional data. Machine learning models can integrate somatic mutations, copy-number changes, gene expression, epigenetic marks, and microenvironmental features to identify actionable subgroups and novel biomarkers predictive of prognosis or response. AI-driven approaches also support discovery of neoantigens and personalized immunotherapy targets by evaluating tumor mutational landscapes and peptide–MHC binding probabilities at scales intractable for conventional methods.[2][3][4][5][7][8]

In the clinic, AI is used to match patients to targeted therapies or clinical trials based on complex genomic signatures rather than single mutations, aligning with hyper-personalized medicine trends. For example, predictive models can stratify patients with non-small cell lung cancer according to their likelihood of benefiting from immunotherapy, enabling more rational allocation of costly treatments and limiting unnecessary toxicity. Multi-omics integration frameworks that merge genomic, transcriptomic, proteomic, and radiomic data are under active development and may soon provide holistic tumor "avatars" that inform optimal combinations and sequences of therapies.[1][3][4][5][7][8][2]

AI in treatment planning and clinical decision-support

AI-enabled clinical decision-support systems (CDSS) are being deployed to help clinicians navigate increasingly complex treatment options in medical, surgical, and radiation oncology. By aggregating EHR data, laboratory results, imaging, pathology, and genomics, these platforms generate evidence-based treatment suggestions tailored to individual patient profiles. Studies have shown that such systems can improve concordance with guidelines and multidisciplinary tumor board recommendations while reducing time spent on manual data review. In radiation oncology, deep learning models optimize dose distributions and organ-at-risk sparing, streamlining planning workflows and potentially improving toxicity profiles.[3][5][7][8]

Beyond static recommendation engines, emerging "agentic" AI systems act as semi-autonomous assistants that continuously monitor patient trajectories, flag concerning trends, and propose adjustments to therapy plans. For example, AI-driven predictive analytics can forecast the risk of severe treatment-related adverse events or unplanned hospitalizations, enabling pre-emptive supportive interventions. Large language models fine-tuned on oncology guidelines and trial data are being piloted to assist clinicians in summarizing complex records and exploring "what-if" scenarios, although their use at the point of care remains cautious due to reliability and liability concerns.[9][5][6][7][8][1][2][3]

AI in clinical trials and population-level oncology

A major challenge in oncology is the slow, expensive process of translating scientific discoveries into effective treatments through clinical trials. AI is now being applied across the trial lifecycle to accelerate this pipeline. Automated patient-matching systems mine EHRs and pathology reports to identify eligible participants based on nuanced inclusion and exclusion criteria, improving accrual and representativeness. Predictive models can simulate trial outcomes under different designs, helping sponsors prioritize promising interventions and optimize endpoints. Real-time monitoring and anomaly detection algorithms enhance data quality and safety oversight, potentially reducing trial duration and costs.[5][8][3]

At the population level, AI-driven analytics support cancer surveillance, resource planning, and health-equity efforts. Health systems and payers are leveraging machine learning to forecast incidence trends, identify geographic or demographic disparities, and evaluate the impact of screening policies or novel therapies on outcomes and costs. These initiatives dovetail with broader trends in data-driven healthcare and agentic AI for system-level decision-making, with the ultimate goal of aligning oncology services with evolving population needs.[4][6][8][1][9]

Comparison of AI-driven and traditional methods

The following table contrasts AI-driven approaches with traditional non-AI methods across key oncology domains, highlighting performance, workflow, and evidence considerations based on recent literature and reports.[7][8][2][3][5]

Table 1. Selected contrasts between AI-driven and traditional approaches in oncology

Domain	Traditional methods (non-AI)	AI-driven approaches in oncology
Cancer screening	Human-read mammography, CT, colonoscopy; variable sensitivity and specificity; limited quantitative analysis.[3][5][8]	Deep learning for lesion detection and risk stratification; improved accuracy in retrospective studies; automated quantification and triage.[2][3][5][8]
Radiology reporting	Manual lesion measurement, qualitative descriptors; time-consuming; inter-observer variability.[3][5][8]	Automated segmentation, radiomics extraction, standardized reporting; reduced variability; potential workflow gains.[3][5][8]
Pathology and biomarkers	Visual grading, limited manual quantification; sequential IHC/molecular tests.[3][7][8]	Whole-slide deep learning; microenvironment quantification; inference of molecular alterations from H&E; integrated biomarker discovery.[3][5][7][8]
Genomics interpretation	Rule-based variant curation; single-marker decisions; labor-intensive trial matching.[2][7][8]	ML models integrating multi-omics; prediction of therapy response; automated trial matching and patient stratification.[3][5][7][8]
Treatment decision-making	Guideline-based, experience-driven; manual chart review; tumor boards with limited data integration.[3][5][8]	AI-powered CDSS aggregating EHR, imaging, pathology, genomics; scenario simulation; agentic monitoring and alerts.[3][5][7][8]
Clinical trial operations	Manual eligibility screening; static designs; delayed safety signal detection.[3][5][8]	Automated patient matching; adaptive design support; real-time analytics for safety and data quality.[3][5][8]

Discussion

AI is poised to transform oncology by enhancing the precision, speed, and scalability of critical tasks across the cancer care continuum, yet its impact will depend on how effectively current challenges are addressed. One of the foremost issues is data quality and representativeness: many high-performing models are trained on datasets from single institutions or regions, raising concerns about generalizability and potential exacerbation of existing disparities when deployed in more diverse populations. Addressing this requires large, multi-institutional consortia, standardized data curation pipelines, and careful auditing for performance across subgroups defined by age, sex, ethnicity, and socioeconomic context. Equally important is ensuring that AI systems are integrated into workflows in ways that augment rather than burden clinicians, with clear user interfaces and explanation mechanisms aligned to clinical reasoning.[6][8][9][2][3][5][7]

Explainability and trust remain persistent concerns, particularly for deep learning systems operating as “black boxes” in high-stakes diagnostic or therapeutic decisions. While post-hoc interpretability tools (e.g., saliency maps, feature-importance rankings) can provide partial insight, many experts argue for design strategies that balance performance with inherent transparency. Regulatory frameworks are evolving to address these issues, with authorities exploring pathways for adaptive, learning systems and expectations for real-world monitoring and post-market surveillance. Ethical considerations—including informed consent, data governance, accountability when errors occur, and the impact of automation on professional roles—must be addressed through multidisciplinary collaboration among clinicians, data scientists, ethicists, patients, and regulators.[8][9][3][5][6]

Looking ahead, several trends are likely to shape the next phase of AI in oncology. First, foundation models trained on massive multimodal medical datasets, including imaging, pathology, and text, may provide versatile backbones that can be adapted to specific cancers and institutions with relatively little labeled data. Second, the convergence of AI with precision and hyper-personalized medicine—through multi-omics integration, longitudinal digital phenotyping, and “digital twin” representations of patients—could enable dynamic, individualized treatment strategies that evolve as tumors and hosts change over time. Third, agentic AI systems capable of proactive monitoring and complex task orchestration may extend beyond decision-support to full care-pathway optimization, though this will require careful governance and clear boundaries for autonomy.[1][9][2][4][6][7][8]

At the same time, it is important to temper expectations and recognize that many AI applications remain in early or experimental stages, with limited prospective, randomized evidence demonstrating impact on hard clinical endpoints such as overall survival or quality of life. Lessons from earlier technologies—such as computer-aided detection systems that did not consistently improve outcomes when first deployed—underscore the need for rigorous evaluation, appropriate implementation strategies, and continuous performance monitoring. Ultimately, AI should be framed as a tool that complements human expertise rather than a replacement; its most meaningful contributions will likely arise when it is embedded within multidisciplinary, patient-centered models of cancer care.[3][5][7][8]

Conclusion

AI in oncology stands at a pivotal moment, with compelling demonstrations of capability across screening, diagnosis, biomarker discovery, and treatment planning, yet with substantial work still required to translate these advances into consistent, equitable improvements in patient outcomes. By enabling more sensitive detection of early-stage cancers, extracting rich quantitative signatures from radiology and pathology, and orchestrating complex genomic and clinical data into actionable insights, AI is reshaping what is possible in precision and hyper-personalized cancer care. The next decade will be defined less by algorithmic breakthroughs than by progress in data governance, validation, regulation, and workflow design, determining whether AI systems become trusted partners in oncology or remain isolated pilot projects. If developed and deployed responsibly—anchored in multidisciplinary collaboration, robust evidence, and a focus on equity—AI has the potential to transform oncology from reactive treatment of advanced disease into a proactive, continuously learning discipline that delivers longer, healthier lives for people with cancer worldwide.

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