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Artificial Intelligence in Health

BRIEF REPORT

A scope of the literature on artificial intelligence in oncology

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Abstract

Artificial intelligence (AI) is transforming healthcare and is increasingly applied across the cancer care continuum. However, prior studies of its use have focused on relatively narrow applications. This scoping review characterizes the current landscape of AI applications in oncology published over the past five years. A two-part literature search was conducted in November 2024. First, nine high-impact journals were manually reviewed for articles published from November 2019 to November 2024 containing the term "artificial intelligence." Second, a structured PubMed search using "artificial intelligence" AND "cancer" was performed, limited to the same period and filtered by study type, to classify studies by their primary area of application. Of 1,305 records screened, 575 studies met the inclusion criteria. Most studies spanned multiple medical subspecialties (n = 154, 27%) or focused on cancer detection (n = 145, 25%). The most frequently studied tumor categories were multiple tumor types (16%), breast (14%), genitourinary (13%), lower gastrointestinal cancers (12%), and lung (12%). Radiomics (n = 153, 27%) and unstructured clinical data (n = 123, 21%) were the most common data sources. The most common primary applications were predictive modeling (n = 157, 27.3%) and biomarker development (n = 156, 27.1%). Current AI research in oncology is dominated by a focus on cancer therapy and diagnosis. Future research requires prospective, multi-institutional validation and evaluation frameworks that incorporate factors such as clinical impact, workflow integration, cost-effectiveness, and ethics. Collaboration among patients, clinicians, ethicists, and healthcare leaders will be key to prioritizing research into underrepresented cancer types, mitigating AI bias, and ensuring that AI innovations are clinically meaningful and sustainable.

Keywords: Artificial intelligence; Oncology; Cancer therapy

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1. Introduction

Artificial intelligence (AI) is transforming healthcare.[1,2] In oncology, where care is complex and data-rich, AI applications have proliferated across the cancer care continuum—from risk assessment and screening to diagnosis, treatment selection, and survivorship.[3-5] Recent advances in machine learning, deep learning, and large language models have further expanded the potential utility of AI, enabling the integration of multi-modal data and real-time clinical decision support.[6]

Despite the promise of AI in oncology, its adoption and impact remain highly variable.[7-9] Prior studies have often focused on single specialties, tumor types, or narrow applications, limiting the ability to understand broader trends. Moreover, AI tools are increasingly being developed not only for clinicians but also as patient-facing interventions, administrative aids, and research accelerators.[10,11] As the number and diversity of AI applications in oncology rapidly grow, there is a need to map the current landscape, identify gaps, and characterize areas of innovation.

To address this gap, we conducted a scoping review of the literature on AI applications in oncology published over the past five years (November 2019 to November 2024). The purpose was to provide an overview of how AI is being used in cancer care, highlight its clinical integration, summarize accomplishments, and identify priorities for future research.

2. Methods

This study was designed as a scoping review to characterize the breadth, methodological heterogeneity, and conceptual trends of AI applications in clinical oncology. We conducted a two-part literature search in November 2024 to identify studies published within the preceding five years. First, we manually searched high-impact journals—*Journal of the American Medical Association* (*JAMA*), *JAMA Oncology*, *The Lancet*, *The Lancet Oncology*, *The Lancet Digital Health*, *New England Journal of Medicine* (*NEJM*), *NEJM AI*, *Journal of Clinical Oncology (JCO)*, and *JCO Clinical Cancer Informatics*—for articles published in the past five years (November 2019 to November 2024), using the keyword "artificial intelligence." Second, we conducted a structured PubMed search on November 30, 2024, using the terms "artificial intelligence" AND "cancer," limited to the past five years, and filtered by study type (clinical study, clinical trial, observational study, or randomized controlled trial). We then manually reviewed results and excluded review articles, technical papers reporting non-clinical outcomes, and non-English publications. This methodology enables a broad mapping of the evidence base, clarifying appropriate inferences for the current state of the field while identifying specific gaps to guide future systematic reviews and research standardization.

For each included study, we extracted the following data: cancer type, medical specialty, type of input data, main AI task, outcome of interest, trial design, and primary application. We applied a structured categorization framework to classify studies by their primary area of application.

AI tasks were classified as (i) patient-interfacing, (ii) cancer screening/diagnosis/risk stratification, (iii) cancer therapy, and (iv) research applications. Primary applications of AI tools were categorized as: (i) increasing efficiency or automating existing clinical processes, (ii) improving quality of clinical care, (iii) increasing sensitivity of tests, (iv) developing novel AI biomarkers, and (v) developing predictive models.

3. Results

A total of 1,066 articles were identified through the PubMed search, and 239 articles were identified through the journal search. After removal of duplicates and unrelated articles, 575 articles were available for analysis (Figure 1). Forty-four studies (7.7%) were randomized controlled trials evaluating AI in clinical settings.

3.1. Healthcare task

Artificial intelligence applications spanned patient-interfacing tools, cancer screening and diagnosis, cancer therapy, and research. A total of 575 studies were categorized by healthcare tasks. The largest group focused on cancer therapy applications for clinical decision-making, including prognostic modeling, prediction of treatment side effects, and treatment outcomes (n = 213, 37%). Cancer screening and diagnosis accounted for 151 studies (26%), while research applications such as data extraction, summarization, and novel analyses comprised 105 studies (18%). Efficiency and quality of care were represented by 75 studies (13%). Fewer studies examined patient-facing or administrative tools (n = 15, 3%), drug development or clinical trial support (n = 12, 2%), and synthetic data or technical deployment (n = 4, < 1%). Task categories and subcategories are provided in Table A1.

3.2. Studies by medical subspecialty

The studies encompassed a broad range of oncology specialties. The majority of studies involved multiple specialties (n = 154, 27%) or focused on cancer detection (n = 145, 25%). Other represented subspecialties included medical oncology, radiology, and radiation oncology (Figure 2A).

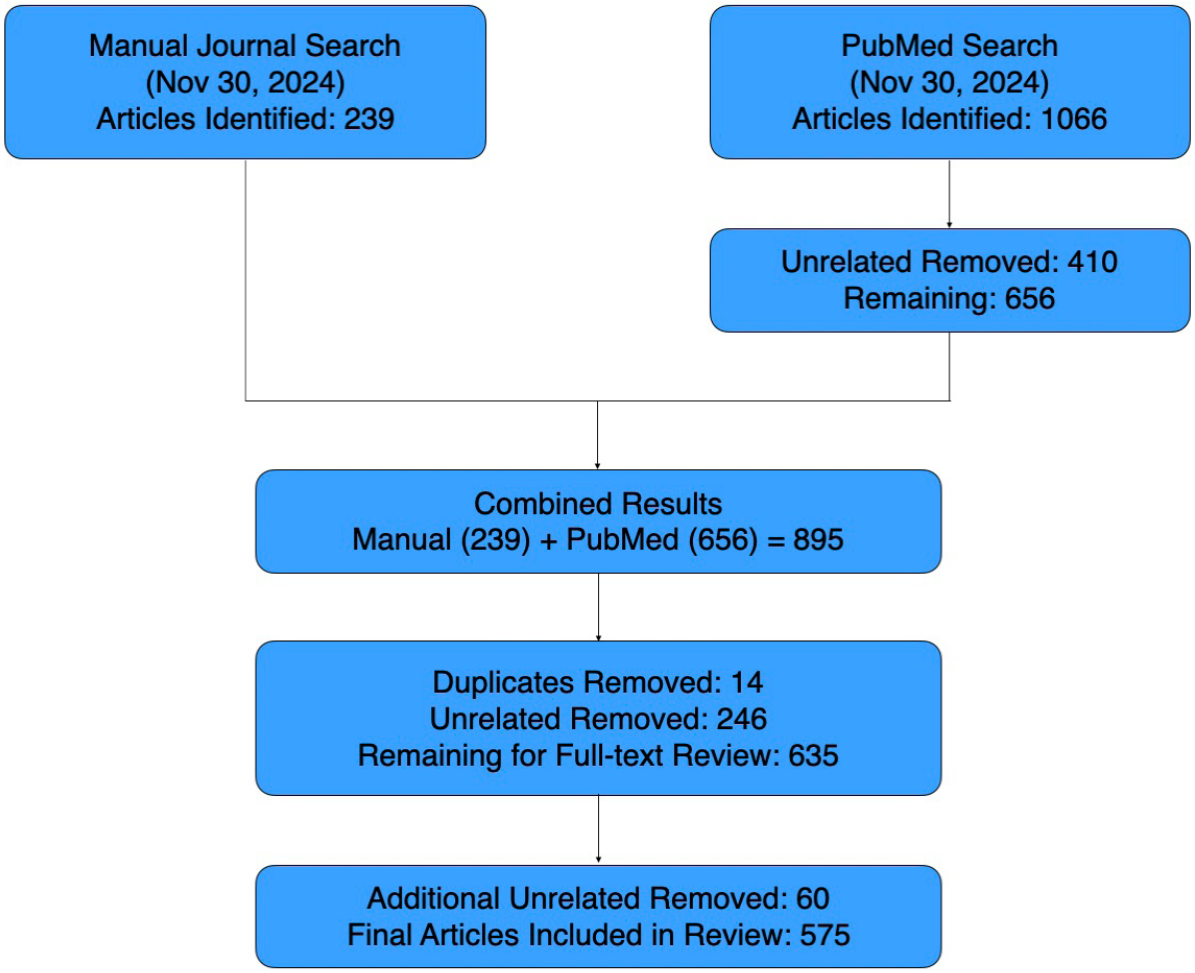


Figure 1. CONSORT flow diagram of study selection for this scoping review of artificial intelligence applications in oncology

3.3. Studies by tumor type

Regarding tumor type, 93 studies (16%) addressed multiple tumor types. Breast cancer (n = 80, 14%), genitourinary cancers (n = 76, 13%), lower gastrointestinal (GI) malignancies (n = 70, 12%), and lung cancer (n = 68, 12%) were also among the most frequently studied tumor types (Figure 2B).

3.4. Data source

Radiomics (n = 153, 27%) was the most frequently used data source for developing AI tools. Unstructured clinical databases (n = 123, 21%), such as free-text clinical notes from electronic health records, were the next most common data source. Video/photo-based imaging data (n = 72, 13%) and a combination of multiple data sources (clinical data, laboratory data, digital pathology, radiographic images) (n = 53, 9%) were also used (Figure 2C).

3.5. Primary application

Across the 575 reported applications, the most common primary applications were predictive modeling (n = 157, 27.3%) and biomarker development (n = 156, 27.1%). Efficiency-related outcomes accounted for 121 studies (21.0%), while detection sensitivity (n = 67, 11.7%) and quality of care improvements (n = 67, 11.7%) were less frequent. Administrative tasks, drug development outcomes, and other endpoints each comprised fewer than 10 studies (<2%) (Figure 3).

4. Discussion

Most studies on AI applications in oncology focus on cancer therapy and diagnostic accuracy in data-rich fields such as radiology and pathology. In addition, we observed that studies disproportionately emphasize certain tumor types, including breast, genitourinary, and GI cancers,

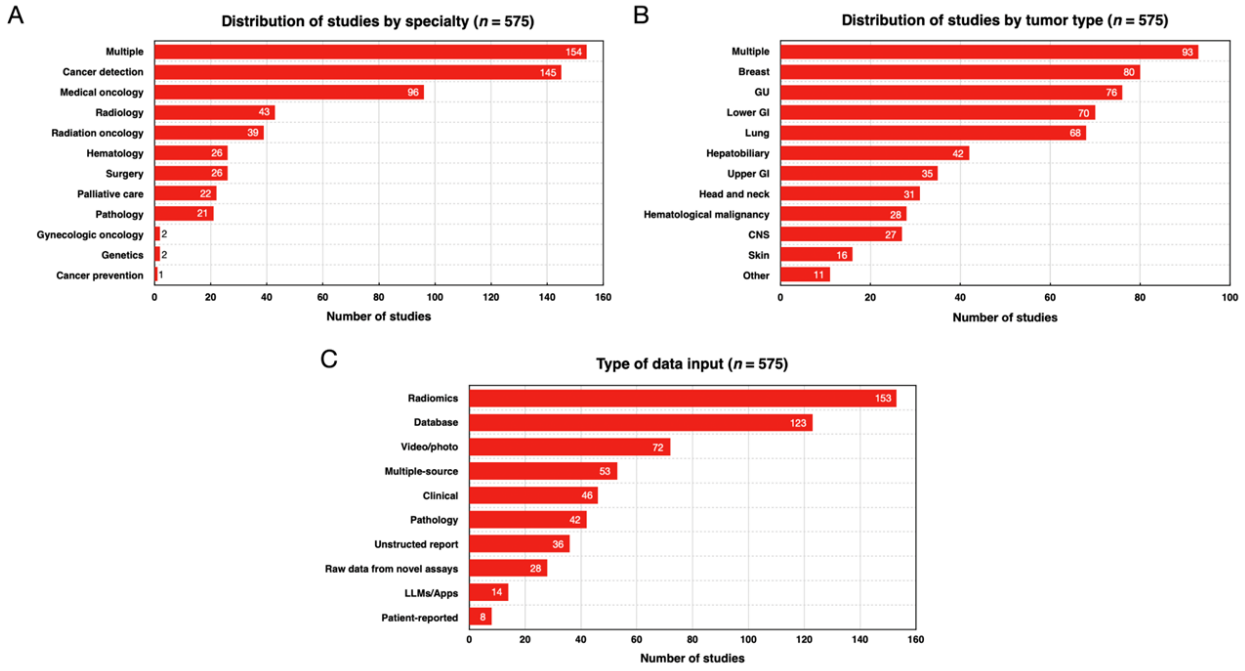


Figure 2. Number of studies by (A) medical specialty, (B) tumor type, and (C) input data.
Abbreviations: CNS: Central nervous system; GI: Gastrointestinal; GU: Genitourinary; LLMs: Large language models.

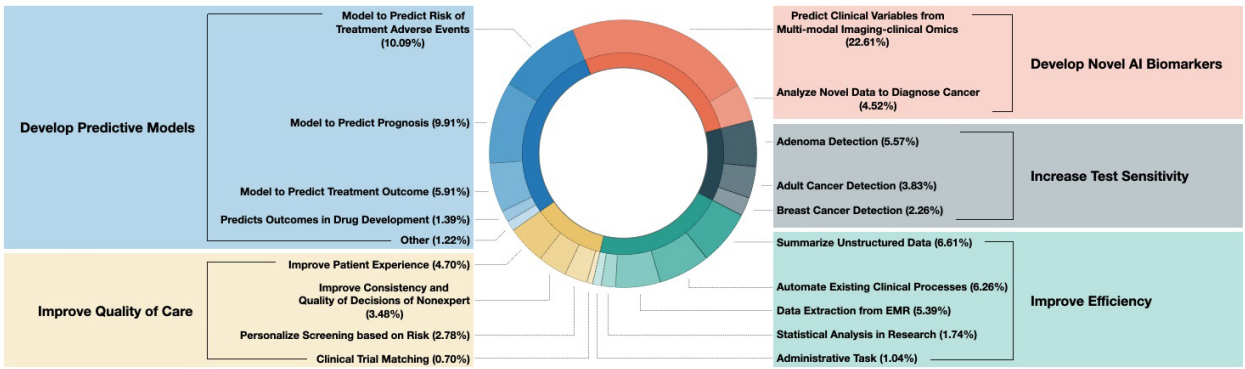


Figure 3. Studies categorized by primary application

while other applications, such as gynecologic cancers, genetic predispositions, and cancer prevention, remain understudied. There is a predominance of nonrandomized studies, highlighting the need for prospective, multi-institutional validation and evaluation frameworks that measure not only accuracy but also clinical impact, workflow integration, cost-effectiveness, and ethical considerations.[12,13] Additionally, no studies explicitly addressed AI bias in oncology, and few studies explored AI applications aimed at improving patient experience and health system performance. Furthermore, most studies involved clinician participants and research teams primarily, with limited inclusion of patients, ethicists, or health system leaders. Since the initial mapping of the AI oncology landscape, the field has rapidly evolved. Patient-facing applications have expanded through generative AI agents that serve as primary patient navigators. Emerging tools are now targeting high-burden workflows such as prior authorization and clinical documentation. However, a critical trend in this 2025–2026 expansion is that many new applications are being deployed as commercial software without accompanying peer-reviewed publications based on prospective data. AI technologies are also increasingly used to improve clinical care by integrating social determinants of health, for example, identifying patients at higher risk of financial toxicity due to treatment, which

could, in turn, be used to identify resources for patients experiencing financial toxicity.[14] Similarly, non-clinical healthcare data, such as housing, transportation, and/or employment status, are being leveraged to determine a patient's ability to access care. However, validation of models using these data remains limited, as current models often cannot fully replicate complex clinical decision-making.[15]

5. Conclusion

Artificial intelligence in oncology is transitioning from proof-of-concept studies to real-world clinical implementation that measures patient outcomes and experiences. The next phase of research in AI oncology must be underpinned by evaluation frameworks that go beyond accuracy metrics. It is essential to consider factors such as the clinical impact of AI applications, their integration into existing workflows, cost-effectiveness, and the ethical implications of their use. Future research should prioritize underrepresented cancer types, actively address potential biases in AI training data, and explore applications of AI that extend beyond the clinical team to include communities, patients, policymakers, and healthcare leaders. Such collaboration will be essential to ensure that AI advancements are not only innovative but also meaningful, sustainable, and equitable.

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Conflict of interest

The authors declare that they have no competing interests.

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Ethics approval and consent to participate

Not applicable.

Consent for publication

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Availability of data

Not applicable.

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Appendix

Table A1. Studies of AI in oncology are categorized by healthcare task, with examples

Healthcare task	Examples	No. of studies, *n* (%)
Patient-interfacing tool		
Chatbot/LLM	An AI chatbot that gives recommendations, answers questions, or assists in symptom management	9 (2)
Cancer screening and diagnosis		
Cancer screening		
Improve the efficiency and accuracy of cancer screening programs	(i) AI-assisted endoscopy for adenoma detection (ii) AI-assisted interpretation of breast imaging (mammogram, US, MRI)	45 (8)
Personalize screening	(i) Identify high-risk patients (ii) Predict individual cancer risk (iii) Determine smoking status in EHR for lung cancer screening	16 (3)
Cancer diagnosis		
Improve accuracy and consistency in interpreting radiographic, endoscopic, and dermoscopy images to support decision-making	(i) Identify retinoblastoma on fundus images (ii) Develop a clinicoradiomic nomogram to identify malignant pulmonary nodules (iii) Identify skin cancer on dermoscopy images (iv) Identify hepatocellular carcinoma on liver imaging (v) Identify bladder cancer on cystoscopy	66 (11)
Increase the rate of cancer detection during biopsy	(i) AI-assisted prostate biopsy (ii) AI-assisted endoscopy	16 (3)
Large data		
Identify cancer patients	Identify patients with pancreatic cancer in a large insurance database	4 (1)
Identify high-risk patients	Predict the 10-year risk of 13 cancers based on the biobank	4 (1)
Cancer therapy		
Clinical decision making		
Novel use of data to predict clinical variables	(i) Predict extranodal extension or lymphovascular invasion from imaging (ii) Predict the genetic signature of a brain tumor from imaging (iii) Predict BRAF mutation based on clinicohistologic data (iv) Predict the Gleason grade from the MRI prostate	64 (11)
Predict the individual risk of side effects to cancer treatment	(i) Predict lenalidomide toxicity (ii) Predict severe hand-foot syndrome (iii) Predict risk of radiation pneumonitis (iv) Predict hospitalization during chemoradiation	58 (10)
Prognostic models to assist decision-making	(i) Predict 1-year OS (ii) Predict death within 7 days (iii) Predict 10-year risk of metastases (iv) Predict early recurrence	57 (10)
Predictive models for treatment outcomes	(i) Predict response to neoadjuvant chemotherapy (ii) Predict response to immunotherapy (iii) Gene signature to predict paclitaxel survival benefit (iv) cfDNA to predict early failure of ADT in prostate cancer	34 (6)

(*Cont'd...*)

Table A1. ***(Continued)***

Healthcare task	Examples	No. of studies, *n* (%)
Efficiency and quality of care		
Increase efficiency of routine clinical care	(i) Treatment planning for radiotherapy (ii) Predict radiotherapy dose distribution (iii) AI-assisted contouring of brain MRI (iv) Grade kidney cancer pathology	36 (6)
Improve the quality of routine clinical care	(i) Stage rectal cancer based on imaging (ii) Detect hypermetabolic tumor sites on PET (iii) Improve radiation dose prediction	20 (3)
Improve patient experience	(i) Analyze symptoms related to endocrine therapy from patient forums (ii) Identify lymphedema in EHR (iii) Identify patients with high financial burden from the EHR (iv) Reduce the scan time of MRI by reconstruction of diffusion-weighted imaging	19 (3)
Administrative	(v) Predict surgery duration (vi) Draft insurance denial appeal letter	6 (0)
Research		
Summarize	(i) Structure pathology report for cancer registry (ii) Classify relevant versus irrelevant publications (iii) Detect reportable tumors in the pathology database	38 (7)
Data extraction	(i) Identify treatment sequence in the discharge database (ii) Classify cancer stage in claims data (iii) Extract ECOG performance status from clinical notes (iv) Identify pregnancy after breast cancer in the EHR	31 (5)
Identify patterns in novel data	(i) ctDNA multiomics fusion analysis to predict survival in breast cancer (ii) Identify an immunologic signature to predict graft versus host disease (iii) Identify cancer-related plasma proteins to detect neuroendocrine tumors (iv) Diagnose pancreatic cancer based on a serum biomarker panel	26 (5)
Outcomes research	(i) Develop a predictive model for lung cancer mortality with SEER data (ii) Identify prognostic and predictive factors in the clinical trial database (iii) Compare the effectiveness of lumpectomy versus mastectomy with SEER data	10 (2)
Drug development	(i) Identify predictive biomarkers from postmarketing surveillance data (ii) Predict clinical trial outcomes from publicly available survival data	8 (1)
Clinical trial	Clinical trial matching tool	4 (1)
Synthetic data	Generate synthetic clinical trial data for a survival prediction model	3 (1)
Technical	Transport machine learning tools between clinical sites	1 (0)

Abbreviations: ADT: Androgen deprivation therapy; AI: artificial intelligence; BRAF: B-Raf proto-oncogene; cfDNA: Cell-free DNA; ctDNA: Circulating tumor DNA; ECOG: Eastern Cooperative Oncology Group; EHR: Electronic health records; LLM: Large language model; MRI: Magnetic resonance imaging; OS: Overall survival; PET: Positron emission tomography; RT: Radiotherapy; RWD: Real-world data; SEER: Surveillance, Epidemiology, and end results; US: Ultrasound.