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Multimodal Artificial Intelligence in Oncology: Integrating Radiomics, Pathomics, and Genomics

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ABSTRACT

The emergence of artificial intelligence (AI) has fundamentally transformed modern oncology by enabling the computational interpretation of increasingly complex biomedical datasets derived from radiology, digital pathology, genomics, transcriptomics, and electronic health records. The integration of these heterogeneous data sources has facilitated the development of multimodal AI frameworks capable of generating biologically meaningful and clinically actionable insights across the entire cancer care continuum. Unlike unimodal computational approaches that analyze isolated data modalities, multimodal AI combines radiomics, pathomics, and genomics to comprehensively characterize tumor heterogeneity at anatomical, histopathological, molecular, and temporal levels. Recent advances in deep learning, transformer architectures, self-supervised learning, and foundation models have substantially enhanced the capacity of multimodal systems to identify latent biological patterns associated with tumor initiation, disease progression, therapeutic resistance, and patient survival. These technologies are increasingly being applied to early cancer detection, molecular subtyping, prognostic risk stratification, immunotherapy response prediction, and precision therapeutic decision-making. Despite these advances, several translational challenges remain, including inadequate data harmonization, algorithmic bias, limited model interpretability, regulatory uncertainty, and the lack of large-scale prospective clinical validation. In addition, ethical considerations surrounding data governance, privacy preservation, and equitable implementation continue to influence the clinical adoption of AI-driven oncology solutions. This review critically examines the evolution of multimodal AI in oncology, with particular emphasis on radiomics, pathomics, and genomics integration strategies, transformer-based architectures, explainable AI, and multimodal fusion techniques. The article further explores contemporary clinical applications, translational challenges, and emerging opportunities involving foundation models and federated learning within precision oncology. Collectively, multimodal AI represents a transformative paradigm with the potential to redefine oncologic diagnosis, personalize therapeutic interventions, strengthen clinical decision support, and accelerate the advancement of precision cancer medicine.

Keywords: Multimodal artificial intelligence; oncology; radiomics; pathomics; genomics; precision medicine; deep learning; transformer models; explainable AI; multi-omics integration.

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1. Introduction

Cancer remains one of the leading causes of morbidity and mortality worldwide despite major advances in molecular biology, targeted therapeutics, and immunoncology. The biological complexity of malignant diseases arises from dynamic interactions among genomic instability, epigenetic modifications, microenvironmental remodeling, and spatiotemporal tumor heterogeneity that collectively influence disease

progression and therapeutic response.[1,2] Conventional clinical decision-making in oncology has historically relied upon fragmented interpretation of imaging findings, histopathological examination, and limited molecular biomarkers. Although these approaches have significantly improved patient management, they often fail to comprehensively capture the multidimensional architecture of tumor biology.[3] The rapid digitization

of healthcare systems and high-throughput biomedical technologies has generated unprecedented quantities of multimodal cancer data, creating new opportunities for AI-driven computational oncology.

The integration of AI into oncology has accelerated substantially over the past decade because of parallel advancements in computational power, data storage infrastructure, and deep learning algorithms.[4] Modern oncology datasets now encompass radiological imaging, whole-slide pathology images, next-generation sequencing, transcriptomics, proteomics, metabolomics, wearable sensor outputs, and longitudinal electronic health records.[5] Individually, these modalities provide partial representations of tumor phenotypes; however, multimodal AI aims to unify them into coherent predictive frameworks capable of uncovering latent biological relationships inaccessible to human interpretation.[6] This paradigm shift has stimulated growing interest in multimodal foundation models that leverage transformer architectures, self-supervised learning, and attention mechanisms to learn generalized representations across heterogeneous biomedical domains.[7]

Radiomics, pathomics, and genomics constitute the foundational pillars of multimodal computational oncology. Radiomics enables quantitative extraction of imaging biomarkers from computed tomography, magnetic resonance imaging, and positron emission tomography, thereby characterizing intratumoral heterogeneity and treatment-associated phenotypes.[8] Pathomics extends computational pathology by applying machine learning to digitized histopathological slides for automated tissue classification, spatial cellular analysis, and microenvironmental characterization.[9] Genomics and multi-omics integration further provide molecular-level insights into oncogenic signaling pathways, mutational landscapes, immune regulation, and therapeutic resistance mechanisms.[10] The synergistic integration of these modalities has demonstrated significant promise in improving diagnostic accuracy, prognostic modeling, and therapeutic stratification across multiple malignancies.

Despite impressive technological progress, the implementation of multimodal AI in routine oncology practice remains constrained by substantial methodological and translational challenges.[11] Data heterogeneity, annotation variability, limited interoperability, domain shift, and inadequate external validation continue to limit generalizability across institutions and populations.[12] Moreover, the opaque nature of deep neural networks raises concerns regarding interpretability, fairness, accountability, and regulatory acceptance.[13] Consequently, there is increasing emphasis on explainable AI, federated learning, privacy-preserving computation, and prospective clinical validation frameworks to ensure safe and equitable deployment of AI systems within healthcare environments.[14]

This review comprehensively examines the scientific evolution, computational foundations, clinical applications, and translational implications of multimodal AI in oncology. Particular emphasis is placed on radiomics, pathomics, genomics integration, transformer-based architectures, multimodal fusion

strategies, explainable AI, ethical considerations, and the future development of foundation models for precision cancer medicine.

2. Evolution of Artificial Intelligence in Oncology

The evolution of AI in oncology has progressed through several interconnected computational eras characterized by increasing algorithmic complexity and biological integration. Early oncology AI systems primarily relied on rule-based expert systems and conventional machine learning algorithms designed to support clinical diagnosis and survival prediction.[15] These methods utilized handcrafted features derived from radiological images or clinicopathological variables and employed classifiers such as support vector machines, random forests, and logistic regression. Although these approaches demonstrated moderate predictive capability, their performance was constrained by limited feature representation and poor scalability across heterogeneous datasets.[16]

The emergence of deep learning transformed computational oncology by enabling hierarchical feature extraction directly from raw biomedical data. Convolutional neural networks (CNNs) rapidly became dominant in radiology and pathology because of their ability to automatically identify spatially complex image patterns associated with tumor morphology, vascularity, necrosis, and stromal architecture.[17] Landmark studies demonstrated that CNN-based systems could achieve diagnostic performance comparable to expert radiologists and pathologists in breast cancer, lung cancer, and dermatologic malignancies.[18,19] Simultaneously, advances in genomic sequencing technologies enabled AI-driven analysis of mutational signatures, transcriptomic profiles, and pathway interactions associated with oncogenesis and therapeutic resistance.[20]

Recent years have witnessed a transition from isolated modality-specific models toward integrated multimodal frameworks capable of simultaneously processing imaging, molecular, and clinical data.[21] This transition has been accelerated by transformer architectures originally developed for natural language processing. Vision transformers and multimodal transformers utilize self-attention mechanisms to model long-range dependencies across heterogeneous biomedical features, thereby improving contextual understanding and predictive performance.[22] Foundation models trained on massive multimodal datasets are increasingly capable of transfer learning across cancer types and clinical tasks, raising the possibility of generalized oncology AI systems.[23]

Concurrently, self-supervised learning has emerged as a critical strategy for addressing the scarcity of annotated medical data. By learning latent feature representations through pretext tasks without extensive manual labeling, self-supervised models have demonstrated robust performance in pathology, radiology, and genomics applications.[24] The integration of large language models into oncology workflows has further enabled automated report generation, literature synthesis, and conversational clinical decision support.[25] These developments collectively signify a paradigm shift from narrow predictive algorithms toward comprehensive

multimodal ecosystems capable of supporting precision oncology at scale.

3. Concept of Multimodal Artificial Intelligence

Multimodal AI refers to computational systems designed to integrate heterogeneous data modalities into unified predictive or interpretive frameworks. In oncology, these modalities commonly include radiological imaging, histopathological whole-slide images, genomic sequencing, transcriptomics, proteomics, and clinical metadata.[26] The biological rationale for multimodal integration derives from the intrinsic heterogeneity of tumors, which cannot be fully characterized by any single diagnostic modality. Imaging captures macroscopic anatomical and physiological phenotypes, pathology reveals microscopic architectural organization, while genomic analyses identify molecular alterations driving tumor behavior.[27]

Multimodal AI architectures are generally categorized according to the level of data integration. Early fusion approaches combine raw or low-level features before model training, thereby enabling simultaneous learning across modalities. Intermediate fusion strategies integrate modality-specific embeddings generated through independent subnetworks, whereas late fusion approaches combine independently generated predictions from separate models.[28] Transformer-based architectures have become particularly influential because self-attention mechanisms allow dynamic weighting of modality-specific information while preserving contextual interactions.[29]

The clinical significance of multimodal AI lies in its capacity to model complex cross-scale relationships associated with tumor biology. For example, radiological imaging features may correlate with specific genomic alterations or immune microenvironment states, thereby enabling noninvasive prediction of molecular phenotypes.[30] Similarly, pathomics-derived cellular architecture may reflect transcriptomic signatures associated with metastatic potential or therapeutic response. By integrating these complementary information sources, multimodal AI systems can improve diagnostic precision, prognostic discrimination, and therapeutic selection compared with unimodal approaches.[31]

Another transformative aspect of multimodal AI is its potential to support longitudinal disease monitoring. Cancer progression is inherently dynamic, involving temporal changes in genomic evolution, treatment response, and microenvironmental adaptation. Multimodal frameworks capable of integrating serial imaging, longitudinal molecular data, and clinical outcomes may facilitate adaptive therapeutic strategies and real-time precision medicine.[32] Consequently, multimodal AI is increasingly viewed as a central technological foundation for future learning healthcare systems in oncology.

4. Radiomics in Precision Oncology

Radiomics has emerged as a major component of precision oncology by enabling extraction of high-dimensional quantitative imaging biomarkers from routinely acquired radiological scans.[33] The central premise of radiomics is that medical images contain

latent biological information reflecting tumor heterogeneity, angiogenesis, metabolism, and microenvironmental interactions. Advanced computational pipelines extract textural, morphological, statistical, and wavelet-based features from computed tomography, magnetic resonance imaging, and positron emission tomography to generate quantitative tumor phenotypes.[34]

Deep learning has substantially expanded the scope of radiomics by replacing handcrafted feature engineering with automated representation learning. CNN-based radiomic models can identify subtle imaging patterns associated with molecular subtypes, metastatic potential, and treatment response that are often imperceptible to human observers.[35] In lung cancer, radiogenomic studies have demonstrated associations between CT-derived imaging signatures and EGFR, KRAS, and ALK mutations, thereby enabling noninvasive molecular characterization.[36] Similar approaches have shown promise in glioblastoma, breast cancer, and hepatocellular carcinoma for predicting immune infiltration, hypoxia, and survival outcomes.[37]

The integration of radiomics with clinical and molecular datasets has significantly improved prognostic modeling. Multimodal radiogenomic frameworks combining imaging features with transcriptomic profiles have demonstrated enhanced predictive performance for recurrence and therapeutic response across multiple malignancies.[38] Moreover, temporal radiomics derived from serial imaging enables dynamic assessment of treatment response and tumor evolution during chemotherapy, radiotherapy, or immunotherapy.[39]

Despite considerable progress, radiomics faces substantial reproducibility challenges related to imaging acquisition variability, segmentation inconsistency, and feature instability.[40] Differences in scanner protocols, reconstruction algorithms, and preprocessing pipelines can substantially influence extracted features, limiting generalizability across institutions. Standardization initiatives such as the Image Biomarker Standardisation Initiative and federated learning approaches are therefore essential for reliable clinical translation.[41]

5. Pathomics and Digital Pathology

Digital pathology has revolutionized histopathological analysis by enabling high-resolution digitization of whole-slide images amenable to computational interpretation. Pathomics extends this paradigm through quantitative extraction of spatial, morphological, and cellular features using AI algorithms.[42] Histopathology remains the diagnostic gold standard for most cancers; however, conventional microscopic interpretation is inherently subjective and susceptible to interobserver variability. AI-driven pathomics offers opportunities for standardized, reproducible, and high-throughput tissue analysis.

CNN-based architectures have demonstrated remarkable capability in automated tumor detection, grading, and segmentation across diverse malignancies.[43] Deep learning models trained on whole-slide images can identify complex tissue patterns associated with tumor aggressiveness, lymphovascular invasion, and stromal remodeling. More recently, transformer-based pathology models have enabled improved contextual understanding

of spatial cellular interactions within the tumor microenvironment.[44]

An important advance in pathomics involves spatial characterization of immune infiltration and tumor-stroma interactions. AI systems can quantify tumor-infiltrating lymphocytes, macrophage populations, and vascular architecture to infer immunological states associated with response to immune checkpoint inhibitors.[45] Integration of pathomics with transcriptomic and proteomic data has further facilitated identification of novel biomarkers associated with immune evasion and therapeutic resistance.[46]

Foundation models pretrained on massive pathology image repositories are increasingly being adapted for downstream oncology tasks through transfer learning.[47] These models enable efficient generalization across tissue types while reducing annotation requirements. Self-supervised learning strategies have proven particularly effective in pathology because manually labeled datasets are often limited and expensive to generate.[48]

Nevertheless, substantial translational barriers remain. Whole-slide images are extremely large and computationally demanding, requiring specialized hardware and efficient tiling strategies.[49] Additionally, staining variability, scanner heterogeneity, and limited interoperability between digital pathology systems complicate model standardization and external validation. Prospective multicenter studies are therefore necessary to establish clinical reliability and regulatory acceptance.

6. Genomics and Multi-Omics Integration

Genomic sequencing technologies have transformed oncology by revealing the molecular architecture of cancer and enabling targeted therapeutic development.[50] AI-driven genomic analysis facilitates interpretation of complex mutational landscapes, transcriptomic signatures, epigenetic modifications, and proteomic interactions associated with tumor initiation and progression. The integration of multi-omics datasets has become increasingly important because isolated genomic alterations rarely capture the full biological complexity of malignant diseases.

Machine learning models are widely used for mutation detection, molecular subtype classification, and pathway analysis. Deep neural networks can identify nonlinear interactions among genomic variables associated with survival outcomes and therapeutic response.[51] In breast cancer, AI-based transcriptomic analysis has improved prediction of endocrine therapy resistance and metastatic recurrence. Similar approaches have been applied in colorectal cancer, glioma, and melanoma to identify clinically relevant molecular signatures.[52]

The integration of genomics with radiomics and pathomics has generated the emerging field of radiopathogenomics. Multimodal frameworks combining imaging, pathology, and molecular data have demonstrated superior performance for tumor classification, risk stratification, and therapeutic prediction compared with single-modality approaches.[53] Importantly, these models may enable noninvasive inference of molecular phenotypes through imaging or pathology surrogates, thereby reducing the

need for repeated invasive biopsies.

Single-cell sequencing and spatial transcriptomics have further expanded the dimensionality of oncology datasets by enabling characterization of intratumoral heterogeneity and microenvironmental dynamics at unprecedented resolution.[54] AI-based integration of spatial omics with histopathology and imaging may facilitate identification of spatially resolved biomarkers associated with immune escape, clonal evolution, and metastatic dissemination. Such approaches are particularly relevant in immuno-oncology, where spatial organization of immune cells strongly influences therapeutic efficacy.[55]

7. Transformer Architectures and Deep Learning Models in Oncology

Transformer architectures have emerged as a transformative computational framework in oncology because of their ability to model long-range dependencies across heterogeneous data modalities.[56] Unlike CNNs, which rely primarily on local convolutional operations, transformers employ self-attention mechanisms that dynamically prioritize relationships among input features. This capability is particularly advantageous for multimodal oncology applications involving complex interactions among imaging, pathology, molecular, and clinical variables.

Vision transformers have demonstrated competitive performance in radiological and pathological image analysis. In digital pathology, transformer models capture global tissue context more effectively than conventional CNNs, thereby improving tumor grading and biomarker prediction.[57] Hybrid CNN-transformer architectures further combine local feature extraction with global contextual reasoning, enhancing performance across classification and segmentation tasks.

Multimodal transformers integrate embeddings from diverse biomedical modalities into unified latent representations. Cross-attention mechanisms enable the model to learn biologically meaningful interactions between imaging features and genomic signatures.[58] Recent oncology foundation models trained on multimodal datasets have shown encouraging transferability across cancer types and clinical tasks, suggesting the possibility of generalized precision oncology systems.

Large language models are increasingly being integrated into oncology workflows for clinical documentation, evidence synthesis, and decision support.[59] When combined with multimodal inputs, these systems may facilitate automated generation of radiology reports, pathology summaries, and treatment recommendations. However, concerns regarding hallucinations, factual reliability, and clinical accountability remain substantial barriers to implementation.

Self-supervised learning and contrastive learning approaches are also reshaping oncology AI development. These methods enable robust feature learning from unlabeled datasets by maximizing similarity between related samples while distinguishing unrelated examples.[60] Such strategies are particularly valuable in medicine because high-quality annotations are limited, costly, and time-intensive to obtain.

8. Multimodal Data Fusion Strategies

Effective multimodal AI depends fundamentally on robust data fusion strategies capable of integrating heterogeneous biomedical information while preserving biologically meaningful relationships. Fusion methodologies are generally categorized into early, intermediate, and late fusion approaches.[61] Early fusion combines raw input features before model training, allowing comprehensive joint representation learning but often increasing dimensionality and computational complexity. Intermediate fusion integrates modality-specific embeddings generated through independent subnetworks, enabling preservation of modality-specific characteristics while facilitating cross-modal interactions. Late fusion aggregates predictions generated independently by separate models and is often computationally efficient but may overlook latent biological relationships.[62] Attention-based fusion architectures have gained prominence because they dynamically weight modality-

specific contributions according to contextual relevance. Cross-modal attention mechanisms enable models to identify interactions between imaging features and genomic signatures associated with prognosis or therapeutic response.[63] Graph neural networks have additionally emerged as promising tools for multimodal oncology because they can model relational structures among molecular pathways, cellular interactions, and clinical variables. Federated learning represents another important strategy for multimodal AI development. Because cancer datasets are often distributed across institutions and constrained by privacy regulations, federated learning enables collaborative model training without centralized data sharing.[64] This approach enhances model generalizability while preserving patient confidentiality. Nevertheless, challenges related to data heterogeneity, communication efficiency, and institutional bias remain unresolved.

Table 1. Comparison of Radiomics, Pathomics, and Genomics in Oncology

Data Type	Source	AI Techniques	Clinical Applications	Advantages	Limitations
Radiomics	CT, MRI, PET imaging	CNNs, radiogenomics, vision transformers	Tumor detection, response prediction, survival stratification	Noninvasive assessment of tumor heterogeneity	Scanner variability and feature instability
Pathomics	Whole-slide histopathology images	CNNs, transformers, self-supervised learning	Tumor grading, microenvironment analysis, biomarker discovery	High spatial resolution and cellular characterization	Large computational requirements and staining variability
Genomics	DNA sequencing, RNA sequencing, proteomics	Deep neural networks, graph learning, multi-omics integration	Molecular subtyping, targeted therapy prediction, resistance analysis	Mechanistic molecular insights	High dimensionality and limited interpretability

Applications of Multimodal AI in Early Cancer Detection

Early cancer detection remains among the most promising clinical applications of multimodal AI because prognosis is strongly dependent on disease stage at diagnosis.[65] Traditional screening modalities often suffer from limited sensitivity, specificity, or interobserver variability. Multimodal frameworks integrating radiological imaging, pathology, and molecular biomarkers have demonstrated enhanced diagnostic performance across several malignancies. In lung cancer screening, AI systems combining low-dose CT radiomics with genomic and clinical data have improved discrimination between benign and malignant pulmonary nodules.[66] Similarly, multimodal mammography models integrating imaging with genomic risk scores and histopathological features have shown improved breast cancer detection accuracy. Liquid biopsy integration with imaging-based AI further enables minimally invasive detection of circulating tumor DNA and early metastatic dissemination.[67] Foundation models trained on large multimodal screening datasets may eventually facilitate population-level cancer screening with improved scalability and personalization. However, false-positive findings,

algorithmic bias, and insufficient prospective validation remain important concerns that must be addressed before widespread implementation.

9. Tumor Classification

Accurate tumor classification is critical for therapeutic selection and prognostic assessment. Multimodal AI has demonstrated superior capability for molecular subtype prediction compared with conventional clinicopathological approaches.[68] In gliomas, integrated radiopathogenomic models can predict IDH mutation status and MGMT promoter methylation using MRI and histopathology data. Similar frameworks have been developed for breast cancer receptor status classification and colorectal cancer microsatellite instability prediction. The integration of pathology and genomics is particularly important for identifying molecularly defined tumor subgroups with distinct therapeutic vulnerabilities.[69] Deep learning algorithms can infer molecular phenotypes directly from whole-slide images, thereby enabling rapid and cost-effective stratification in resource-limited settings. Multimodal classification systems may ultimately reduce diagnostic uncertainty and support standardized oncology workflows.

10. Prognostic Prediction

Predicting survival outcomes and disease recurrence represents a major challenge in oncology because of substantial interpatient heterogeneity. Multimodal AI systems integrating imaging, pathology, molecular profiles, and clinical variables have consistently demonstrated improved prognostic performance relative to conventional staging systems.[70]

Radiogenomic models can identify imaging signatures associated with aggressive molecular phenotypes and metastatic potential. Pathomics-based analysis of tumor architecture and immune infiltration further provides insights into recurrence risk and therapeutic resistance.[71] Importantly, longitudinal multimodal models incorporating serial imaging and temporal genomic evolution may enable dynamic risk prediction throughout the disease course.

Several studies have shown that transformer-based survival models outperform traditional Cox proportional hazards approaches by capturing nonlinear interactions among multimodal variables.[72] Nevertheless, prospective validation and calibration across diverse populations remain essential before integration into clinical decision-making.

11. Precision Therapeutics

Precision oncology seeks to tailor treatment strategies according to individual tumor biology and patient characteristics. Multimodal AI has become increasingly important for predicting therapeutic response and identifying optimal treatment combinations.[73] Integrated radiomic, pathomic, and genomic signatures can identify patients likely to benefit from targeted therapies, chemotherapy, radiotherapy, or combination regimens.

AI-driven drug response prediction models utilize multimodal molecular data to infer pathway dependencies and resistance mechanisms.[74] In breast and lung cancers, multimodal systems have

demonstrated encouraging performance for predicting response to HER2-targeted therapy, EGFR inhibitors, and immune checkpoint blockade. Such approaches may reduce unnecessary toxicity while improving therapeutic efficacy.

The emergence of digital twins and adaptive treatment modeling further illustrates the translational potential of multimodal AI. By integrating longitudinal clinical, imaging, and molecular data, computational models may eventually simulate treatment trajectories and optimize individualized therapeutic strategies in real time.[75]

12. Immuno-Oncology

Immuno-oncology has transformed cancer treatment through the development of immune checkpoint inhibitors and cellular therapies; however, response rates remain highly variable across patients.[76] Multimodal AI offers opportunities to characterize the complex interactions among tumors, immune cells, and the microenvironment that determine immunotherapy efficacy.

Pathomics-based quantification of tumor-infiltrating lymphocytes and spatial immune organization has shown strong associations with checkpoint inhibitor response.[77] Radiomics can additionally capture imaging correlates of immune activation and tumor inflammation, while transcriptomic analyses identify immunological gene signatures and cytokine networks. Integrating these modalities may improve prediction of response and immune-related adverse events.

Spatial transcriptomics combined with digital pathology has become particularly valuable for understanding immune microenvironment heterogeneity.[78] AI-driven analysis of spatial cellular organization may reveal mechanisms of immune escape and identify novel therapeutic targets. These approaches are expected to play an increasingly important role in the development of next-generation immunotherapies.

Table 2. Recent Applications of Multimodal AI in Different Cancer Types

Cancer Type	Modalities Integrated	AI Model Used	Clinical Outcome	Key Findings	Reference
Lung cancer	CT radiomics + genomics	CNN-transformer hybrid	EGFR mutation prediction	Improved noninvasive molecular classification	[36]
Breast cancer	Mammography + pathology + transcriptomics	Multimodal deep learning	Survival prediction	Enhanced prognostic accuracy	[52]
Glioblastoma	MRI + genomics	Vision transformer	IDH mutation prediction	Accurate molecular subtype inference	[68]
Colorectal cancer	Histopathology + RNA sequencing	Attention-based fusion model	Microsatellite instability detection	Improved therapeutic stratification	[69]
Melanoma	Pathomics + spatial transcriptomics	Graph neural network	Immunotherapy response prediction	Identification of immune microenvironment signatures	[78]

Explainable Artificial Intelligence in Oncology

The increasing complexity of multimodal deep learning systems has intensified concerns regarding transparency and interpretability in clinical oncology.[79] Many high-performing AI models operate as opaque black boxes, limiting clinician trust and regulatory acceptance. Explainable AI seeks to address these concerns by

generating interpretable representations of model reasoning and feature importance.

Several explainability techniques have been applied to oncology AI, including saliency maps, gradient-weighted class activation mapping, SHAP values, and attention visualization.[80] In radiology and pathology, these methods highlight image regions contributing most

strongly to model predictions, thereby facilitating biological interpretation and error analysis. Explainable multimodal models may additionally identify clinically meaningful interactions among imaging, pathology, and genomic features.

Interpretability is particularly important for precision therapeutics because treatment recommendations directly influence patient outcomes. Transparent models may help clinicians understand why specific genomic alterations or imaging patterns are associated with therapeutic sensitivity or resistance.[81] However, current explainability methods often provide only superficial approximations of underlying model behavior. Consequently, further research is needed to develop robust, clinically meaningful interpretability frameworks.

13. Ethical, Regulatory, and Data Privacy Challenges

The integration of multimodal AI into oncology raises complex ethical, legal, and regulatory considerations. Cancer datasets frequently contain highly sensitive genomic and clinical information, creating substantial privacy and security concerns.[82] Data sharing across institutions is often restricted by regulatory frameworks such as the General Data Protection Regulation and the Health Insurance Portability and Accountability Act.

Algorithmic bias represents another major challenge. AI models trained on nonrepresentative datasets may demonstrate reduced performance in underrepresented populations, thereby exacerbating healthcare disparities.[83] Bias can emerge from demographic imbalance, institutional heterogeneity, or unequal access to healthcare resources. Ensuring equitable deployment therefore requires diverse multicenter datasets and continuous fairness evaluation.

Regulatory approval pathways for multimodal AI remain incompletely defined. Dynamic learning systems capable of continuous adaptation challenge conventional medical device regulatory frameworks.[84] Furthermore, determining accountability for AI-assisted clinical decisions remains legally complex. Prospective clinical trials and post-deployment monitoring systems will therefore be essential to establish safety, reliability, and clinical utility.

Federated learning and privacy-preserving computation have emerged as promising solutions for secure collaborative AI development.[85] Differential privacy, homomorphic encryption, and decentralized training approaches may facilitate multicenter model development while minimizing risks associated with centralized data storage.

14. Clinical Translation and Future Perspectives

Although multimodal AI has demonstrated remarkable experimental performance, successful clinical translation requires overcoming several methodological and infrastructural barriers. Most published studies remain retrospective and are conducted using relatively small datasets with limited external validation.[86] Prospective multicenter clinical trials are necessary to establish real-world effectiveness, reproducibility, and cost-effectiveness.

Standardization of data acquisition, annotation, and preprocessing pipelines represents another critical

requirement. Harmonized imaging protocols, pathology workflows, and genomic sequencing standards are essential for reliable model generalization.[87] Interoperability between healthcare systems and AI platforms will additionally determine scalability within routine clinical environments.

The future of multimodal oncology AI will likely be shaped by foundation models trained on massive multimodal biomedical datasets. These systems may support transfer learning across diverse cancer types and clinical tasks while reducing dependence on disease-specific annotations.[88] Integration of large language models with imaging and molecular data could facilitate comprehensive clinical decision support systems capable of synthesizing radiology reports, pathology findings, genomic analyses, and therapeutic guidelines.

Self-supervised learning and generative AI may further accelerate biomarker discovery and drug development. Generative models capable of simulating tumor evolution or predicting therapeutic resistance could inform adaptive treatment strategies and clinical trial design.[89] Similarly, digital twins integrating longitudinal multimodal data may eventually enable real-time precision oncology by simulating individualized disease trajectories.

Importantly, future development must prioritize human-centered AI frameworks that augment rather than replace clinical expertise. Collaborative interaction between oncologists, radiologists, pathologists, bioinformaticians, and AI systems will be essential for safe and effective implementation.[90] Education and workforce training programs must therefore evolve to incorporate computational literacy and interdisciplinary collaboration.

15. Conclusion

Multimodal AI is rapidly transforming oncology by integrating radiomics, pathomics, genomics, and clinical data into unified computational frameworks capable of capturing the multidimensional complexity of cancer biology. Advances in deep learning, transformer architectures, self-supervised learning, and foundation models have substantially improved the capacity of AI systems to support early cancer detection, molecular classification, prognostic prediction, immunotherapy response assessment, and precision therapeutics. The convergence of imaging, pathology, and molecular profiling has generated unprecedented opportunities for biomarker discovery and individualized cancer care.

Despite these advances, major translational challenges remain. Data heterogeneity, limited external validation, algorithmic bias, interpretability concerns, and regulatory uncertainty continue to impede routine clinical implementation. Future progress will require standardized multicenter datasets, explainable and privacy-preserving AI frameworks, prospective clinical trials, and interdisciplinary collaboration between computational scientists and oncology specialists. Ultimately, multimodal foundation models integrated within learning healthcare systems may redefine precision oncology by enabling adaptive, biologically informed, and patient-specific therapeutic decision-making.

References

1. Azizi S, Mustafa B, Ryan F, et al. Big self-supervised models advance medical image classification. *Nature*. 2021;594(7864):104–110. Doi:10.1038/s41586-021-03476-6.
2. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44–56. Doi:10.1038/s41591-018-0300-7.
3. Dosovitskiy A, Beyer L, Kolesnikov A, et al. An image is worth 16×16 words: transformers for image recognition at scale. *arXiv*. 2020. Doi:10.48550/arXiv.2010.11929.
4. Yala A, Lehman C, Schuster T, et al. A deep learning mammography-based model for improved breast cancer risk prediction. *Radiology*. 2019;292(1):60–66. Doi:10.1148/radiol.2019182716.
5. Moor M, Banerjee O, Abad ZSH, et al. Foundation models for generalist medical artificial intelligence. *Nature*. 2023;616(7956):259–265. Doi:10.1038/s41586-023-05881-4.
6. Rajendran LKK. Hematological Malignancy Identification via K-means based ROI Extraction. *International Journal of Clinical Research in Medical Sciences*. 2026;1(2):1-10. Doi:10.67231/kt1w3e73.
7. Kumar RMH. Pan-System Cancer Intelligence: Integrating Blood, Immune, Microbiome, and Tumor Microenvironment Data Using Foundation Models. *Power System Protection and Control*. 2023;51(4):92-100. Doi:10.46121/pspc.51.4.8.
8. Rajendran LKK. Identifying Determinants of Outcome in Post-Radiotherapy Cervical Carcinoma Requiring Adjuvant Surgery. *International Journal of Clinical Research in Medical Sciences*. 2026;1(2):1-10. Doi:10.67231/3acej759.
9. Maradi Hemanth Kumar R. AI-Driven Liquid Biopsy Systems for Early Cancer Detection and Personalized Oncology. *Power System Protection and Control*. 2023;51(4):66-83. Doi:10.46121/pspc.51.4.7.
10. Rajendran LKK. Machine Learning–Driven Symptom-Based Cancer Risk Stratification: A Systematic Review of Clinical Prediction Models and Methodological Rigor. *Int J Drug Deliv Technol*. 2026;16(40s):242-253. Doi:10.25258/ijddt.16.40s.26.
11. Rajendran OK. Bias, Fairness, and Ethical Challenges in Artificial Intelligence: A Comprehensive Review of Causes, Impacts, and Mitigation Strategies. *Scientific Culture*. 2026;12(2.1):13001-13010. Doi:10.5281/zenodo.20374091.
12. Rajendran OK. Clinical Translation of Artificial Intelligence in Oncology: Real-World Validation, Workflow Integration, and Precision Medicine Applications. *Int J Drug Deliv Technol*. 2026;16(49s):956-964. Doi:10.25258/ijddt.16.49s.110.
13. Rajendran LKK. Interpretable Machine Learning for Early Mortality Prediction in Acute Myeloid Leukemia: A Decision Tree–Based Retrospective Cohort Study. *Int J Drug Deliv Technol*. 2026;16(40s):231-241. Doi:10.25258/ijddt.16.40s.25.
14. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24–29. Doi:10.1038/s41591-018-0316-z.
15. Rajendran OK. Generative AI for Synthetic Medical Image Generation in Oncology: Addressing Data Scarcity in AI-Driven Cancer Diagnosis. *Int J Drug Deliv Technol*. 2026;16(49s):1010-1016. Doi:10.25258/ijddt.16.49s.117.
16. Rajendran LKK. Integrated Prognostic Modeling of Tumor Stage, Multimodal Therapy, and Functional Status in Lung Cancer Survival: A Real-World Cohort Study. *Scientific Culture*. 2026;12(5):567-576. Doi: 10.5281/zenodo.20738481.
17. Bommasani R, Hudson DA, Adeli E, et al. On the opportunities and risks of foundation models. *arXiv*. 2021. Doi:10.48550/arXiv.2108.07258.
18. Rajendran LKK. Integrative Pharmacogenomic Analysis of Drug Response Heterogeneity Across Cancer Cell Lines: Insights From Large-Scale GDSC Data. *Scientific Culture*. 2026;12(4):7537-7546. Doi:10.5281/zenodo.12426762.
19. Acs B, Rantalainen M, Hartman J. Artificial intelligence as the next step towards precision pathology. *J Intern Med*. 2020;288(1):62–81. Doi:10.1111/joim.13030.
20. Rajendran OK. Tumor Microenvironment Interaction-Guided Graph Neural Networks for Survival Prediction from Whole-Slide Pathology Images. *Int J Drug Deliv Technol*. 2026;16(49s):481-488. Doi:10.25258/ijddt.16.49s.50.
21. Rajendran LKK. Evaluating the Association of Cancer-Related Risk Factors With Multisystem Health: Insights Into Fertility, Cardiovascular, and Renal Indicators. *Scientific Culture*. 2026;12(4):7520-7527. Doi:10.5281/zenodo.12426760.
22. Rajendran LKK. From Prediction to Precision: An Externally Validated Deep Learning–Based Survival and Adjuvant Therapy Recommendation System for Resected Stage III Non–Small Cell Lung Cancer. *Int J Drug Deliv Technol*. 2026;16(30s):430-438. doi:10.25258/ijddt.16.30s.41.
23. Kumar RMH. Multimodal foundation AI models in precision oncology: Integrating radiomics, pathomics, multi-omics, and clinical intelligence systems. *Power System Protection and Control*. 2024;52(4):189-204. Doi:10.46121/pspc.52.4.16.
24. Rajendran LKK. From Prediction to Practice: A Machine Learning–Based Clinical Decision Support Tool for Bevacizumab Risk Stratification in Oncology. *Int J Drug Deliv Technol*. 2026;16(30s):414-429. Doi:10.25258/ijddt.16.30s.40.
25. Rajendran OK. Self-supervised multimodal Learning for early cancer detection across Imaging and genomics. *Power System Protection and Control*. 2024;52(4):167-178. Doi:10.46121/pspc.52.4.14.
26. Rajendran OK. Explainable AI-Driven Clinical Decision Support Systems in Precision Oncology: Interpretable Models for Multimodal

- Cancer Care. Scientific Culture. 2026;12(2.1):12359-12369. Doi:10.5281/zenodo.20328194.
27. Rajendran LKK. Impact of Treatment Modalities on Fertility, Sexual Function, and Psychological Outcomes in Testicular Cancer Survivors: A Comprehensive Review. *Int J Drug Deliv Technol.* 2026;16(30s):447-453. Doi:10.25258/ijddt.16.30s.43.
 28. Rajendran LKK. Intelligent Omics-Driven Patient Stratification for Cancer Therapeutic Re-profiling. *International Journal of Clinical Research in Medical Sciences.* 2026;1(1):1-11. Doi:10.67231/gv5hck05.
 29. Rajendran LKK. Cancer nanomedicine: utilizing the enhanced permeability and retention (EPR) effect to deliver high payloads of chemotherapeutic agents directly to tumor sites. *Power System Protection and Control.* 2024;52(2):123-129. Doi:10.46121/pspc.52.2.12.
 30. Kather JN, Calderaro J. Development of AI in digital pathology. *Nat Rev Clin Oncol.* 2020;17(10):591–595. Doi:10.1038/s41571-020-00431-0.
 31. Rajendran OK. AI-based radiogenomic Models for predicting immunotherapy response In solid tumors. *Power System Protection and Control.* 2023;51(4):24-37. Doi:10.46121/pspc.51.4.4.
 32. Rajendran LKK. Enhanced Predictive Analytics for Early Malignancy Discovery in Routine Screening. *International Journal of Clinical Research in Medical Sciences.* 2026;1(1):1-10. Doi:10.67231/grams870.
 33. Wan JCM, Massie C, Garcia-Corbacho J, et al. Liquid biopsies come of age: towards implementation of circulating tumour DNA. *Nat Rev Cancer.* 2017;17(4):223–238. Doi:10.1038/nrc.2017.7.
 34. Rajendran OK. Machine Learning-Based Prediction of Chemotherapy Toxicity in Colorectal Cancer: A Personalized Risk Stratification Approach. *Scientific Culture.* 2026;12(5.1):942-952. Doi:10.5281/zenodo.12511075.
 35. Rajendran OK. Federated radiology AI Models for multi-institutional cancer diagnosis Without data sharing. *Power System Protection And Control.* 2023;51(4):38-54. Doi:10.46121/pspc.51.4.5.
 36. Kumar RMH. AI-augmented immuno-oncology: Foundation models for predicting immune response, resistance, and precision immunotherapy. *Power System Protection and Control.* 2024;52(2):193-208. Doi:10.46121/pspc.52.2.18.
 37. Rajendran OK. Deep Reinforcement Learning in Oncology: Advances in Cancer Imaging, Radiotherapy, and Personalized Treatment. *Scientific Culture.* 2026;12(5):597-606. Doi:10.5281/zenodo.1250048.
 38. Rajendran OK. DEEP LEARNING FOR CROSS-MODALITY MAPPING BETWEEN HISTOPATHOLOGY AND RADIOLOGICAL IMAGING. *Power System Protection and Control.* 2025;53(3):313-328. Doi:10.46121/pspc.53.3.21.
 39. Lu MY, Chen TY, Williamson DFK, et al. AI-based pathology predicts origins for cancers of unknown primary. *Nature.* 2021;594(7861):106–110. Doi:10.1038/s41586-021-03512-4.
 40. Rajendran OK. Artificial Intelligence in Oncologic Imaging: Deep Learning, Radiomics, and Clinical Integration for Precision Cancer Diagnosis. *Int J Drug Deliv Technol.* 2026;16(50s):871-880. Doi:10.25258/ijddt.16.50s.92.
 41. Bilal M, Raza SEA, Azam A, et al. Development and validation of a weakly supervised deep learning framework to predict the risk of colorectal cancer recurrence from histology images. *Lancet Oncol.* 2021;22(11):153–163. Doi:10.1016/S1470-2045(21)00430-5.
 42. Rajendran OK. DIGITAL TWIN FRAMEWORKS FOR PERSONALIZED CANCER PROGRESSION MODELING USING LONGITUDINAL DATA. *Power System Protection and Control.* 2025;53(4):486-501. Doi:10.46121/pspc.53.4.33.
 43. Rajendran LKK. Genomic profiling: utilizing Multi-omics data to identify potential Therapeutic targets and resistance markers. *Power System Protection and Control.* 2024;52(4):159-166. Doi:10.46121/pspc.52.4.13.
 44. Rajendran OK. Artificial Intelligence–Driven Multimodal Imaging for Cancer During Pregnancy: Advances in Maternal–Fetal Diagnostics and Precision Oncology. *Int J Drug Deliv Technol.* 2026;16(50s):862-870. Doi:10.25258/ijddt.16.50s.91.
 45. Rajendran LKK. Immunotherapy and cell Therapy: developing CAR-T cell therapies and Other immune-based treatments for cancer and Autoimmune diseases. *Power System Protection and Control.* 2023;51(2):64-77. Doi:10.46121/pspc.51.2.7.
 46. Rajendran OK. FOUNDATION MODEL–DRIVEN PRECISION ONCOLOGY: INTEGRATING MULTI-OMICS, RADIOLOGY, AND CLINICAL DATA FOR PREDICTIVE CANCER CARE. *Power System Protection and Control.* 2024;52(2):154-163. Doi:10.46121/pspc.52.2.14.
 47. Rajendran LKK. Theranostics: integrating Diagnostic imaging agents and therapeutic Drugs into a single multifunctional nano-Platform for real-time monitoring of treatment. *Power System Protection and Control.* 2025;53(2):376-386. Doi:10.46121/pspc.53.2.31.
 48. Rajendran LKK. Mechanisms driving Immunotherapy resistance in colorectal cancer Liver metastases. *Power System Protection and Control.* 2024;52(1):29-37. Doi:10.46121/pspc.52.1.5.
 49. Ching T, Himmelstein DS, Beaulieu-Jones BK, et al. Opportunities and obstacles for deep learning in biology and medicine. *J R Soc Interface.* 2018;15(141):20170387. Doi:10.1098/rsif.2017.0387.
 50. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. *Med Image Anal.* 2017;42:60–88. Doi:10.1016/j.media.2017.07.005.
 51. Hemanth Kumar RM. Integrated Transcriptomic and 3 Learning Framework Identifies a Blood-Based Biomarker Signature for Anthracycline-Induced Cardiotoxicity in Juvenile Cancer Survivors. *Int J*

Drug Deliv Technol. 2026;16(40s):219-230.
Doi:10.25258/ijddt.16.40s.24.
52. Rajendran OK. DeepDRA: A Deep Learning
Framework for Drug Repurposing and Cancer Drug

Response Prediction Using Multi-Omics Data.
Scientific Culture. 2026;12(3):68-77.
Doi:10.5281/zenodo.12326001.