International Journal of Research in Engineering and Management Sciences (IJREMS)
E-ISSN: 3107-7439
Research Article
VOL.: 1, Issue: 7, December 2025

Artificial Intelligence for Real-Time Oncology: Continuous Learning Systems for Personalized Cancer Care

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ABSTRACT:
Artificial intelligence (AI) is transforming oncology from a reactive discipline into a continuously adaptive and learning healthcare ecosystem. Traditional cancer management relies on episodic clinical assessments, static treatment protocols, and infrequent updates of patient information, often limiting the ability to respond promptly to rapidly evolving tumor biology. Recent advances in continuous learning systems, multimodal foundation AI models, digital pathology, radiomics, multi-omics, wearable technologies, liquid biopsy, electronic health records, and real-world clinical data have created unprecedented opportunities for real-time oncology. These intelligent systems continuously integrate heterogeneous biomedical information to generate dynamic patient-specific computational representations that evolve alongside disease progression, therapeutic response, and physiological changes. Unlike conventional machine learning algorithms that remain fixed after deployment, continuous learning systems iteratively update predictive models using newly acquired clinical evidence while supporting adaptive diagnosis, treatment optimization, toxicity prediction, recurrence monitoring, and personalized survivorship care. Advances in transformer architectures, graph neural networks, reinforcement learning, federated learning, agentic AI, retrieval-augmented generation, digital twins, and large language models are further expanding the capabilities of real-time computational oncology. Despite remarkable progress, important challenges remain regarding data harmonization, computational scalability, explainability, cybersecurity, regulatory validation, algorithmic stability, and ethical governance. This review provides a comprehensive overview of AI-driven real-time oncology, emphasizing continuous learning systems, computational architectures, clinical applications, implementation challenges, and future perspectives for personalized cancer care.[1]

Keywords: Real-time oncology, Artificial intelligence, Continuous learning systems, Precision oncology, Foundation models, Digital twins, Multi-omics, Clinical decision support, Personalized medicine, Computational oncology.

Received Date: 5 December 2025; **Accepted Date:** 15 December 2025; **Published Date:** 20 December 2025.

1.Introduction

Cancer is a dynamic biological disease characterized by continuous genetic evolution, epigenetic remodeling, immune adaptation, metabolic reprogramming, and interactions within the tumor microenvironment. These biological processes evolve throughout diagnosis, treatment, remission, recurrence, and metastatic progression, making cancer management an inherently dynamic clinical challenge. Conventional oncology, however, frequently relies on periodic clinical assessments that capture only isolated snapshots of disease status rather than continuously monitoring evolving biological processes.[2]

Modern healthcare generates enormous volumes of heterogeneous biomedical information through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, laboratory investigations, wearable biosensors, liquid biopsy, electronic health records, and patient-reported outcomes. Although each modality contributes valuable clinical insight, isolated interpretation often fails to capture the complexity of tumor evolution in real time.[3]

Artificial intelligence has emerged as a transformative technology capable of integrating these diverse information sources into continuously evolving computational representations of individual patients. Continuous learning systems extend this capability further by updating predictive models as new clinical evidence becomes available, thereby enabling adaptive precision oncology throughout the patient journey.[4]

The convergence of continuous learning AI, multimodal foundation models, digital twins, and real-time clinical intelligence is redefining personalized cancer care through dynamic computational decision-making and adaptive therapeutic optimization.[5]

2.Evolution of Real-Time Oncology

Historically, oncology relied primarily on histopathological diagnosis, anatomical staging, and standardized treatment protocols. While these approaches significantly improved cancer management, they often overlooked the dynamic biological evolution occurring throughout disease progression and therapeutic intervention.[6]

Advances in molecular oncology introduced genomic biomarkers, targeted therapies, and immunotherapy, enabling increasingly individualized treatment selection. Simultaneously, electronic health records, digital pathology, wearable health technologies, and high-throughput sequencing dramatically increased the quantity of available biomedical information.

Artificial intelligence subsequently enabled automated interpretation of complex multimodal datasets, while recent development of continuous learning systems introduced adaptive computational models capable of incorporating newly acquired patient information throughout clinical care.

Today, real-time oncology represents the integration of continuously evolving biomedical data, adaptive artificial intelligence, and personalized clinical decision-making into a unified computational healthcare ecosystem.[7]

3.Continuous Learning Artificial Intelligence

Continuous learning systems differ fundamentally from conventional machine learning algorithms because they continuously update computational knowledge using newly acquired clinical information rather than remaining static after initial training. These adaptive systems learn from evolving patient trajectories, therapeutic responses, disease progression, laboratory investigations, imaging studies, pathology findings, and real-world clinical outcomes.[8]

Foundation AI models provide generalized biomedical representations through large-scale self-supervised learning, whereas continual learning mechanisms enable incremental updating without catastrophic forgetting of previously acquired knowledge. Reinforcement learning further optimizes therapeutic recommendations by continuously evaluating treatment outcomes and adapting future decision-making.

These computational paradigms enable oncology systems to evolve alongside advancing medical knowledge and changing patient biology, thereby supporting increasingly personalized precision medicine.[9]

4.Computational Architecture

Modern real-time oncology platforms consist of interconnected computational layers responsible for multimodal data acquisition, preprocessing, representation learning, continuous model updating, predictive analytics, and intelligent clinical decision support.[10]

The acquisition layer continuously collects radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable sensor data, liquid biopsy results, medication history, physiological monitoring, and electronic health records. Advanced preprocessing pipelines harmonize heterogeneous datasets, normalize imaging studies, encode clinical narratives using natural language processing, and synchronize longitudinal patient information.

Transformer-based foundation models generate generalized patient embeddings, while graph neural networks represent interactions among molecular pathways, immune responses, therapeutic targets, physiological variables, and clinical outcomes. Continuous learning modules update predictive models as new information becomes available, ensuring that computational recommendations remain current throughout patient management.[11]

5.Multimodal Data Integration

Real-time oncology depends upon seamless integration of diverse biomedical modalities into unified patient-centered computational representations. Radiological imaging provides anatomical and functional characterization of tumors, whereas digital pathology reveals microscopic tissue architecture and cellular morphology. Genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, and liquid biopsy contribute complementary molecular insights regarding tumor biology and therapeutic responsiveness.[12]

Wearable biosensors continuously monitor physiological parameters including heart rate, physical activity, sleep quality, and treatment-related symptoms. Laboratory biomarkers, medication history, physician documentation, and electronic health records provide additional clinical context necessary for individualized care.

Artificial intelligence harmonizes these heterogeneous datasets through multimodal transformer architectures, cross-modal attention mechanisms, biological knowledge graphs, and graph neural networks, enabling comprehensive computational understanding of patient-specific disease evolution.[13]

6.Foundation Models for Real-Time Clinical Intelligence

Foundation AI models represent one of the most important technological advances supporting real-time oncology. Unlike conventional task-specific algorithms, foundation models learn generalized biomedical representations from extremely large multimodal datasets before adaptation to specialized oncology applications.[14]

Self-supervised learning enables discovery of latent relationships among radiological imaging, digital pathology, molecular biology, laboratory investigations, and clinical documentation without requiring extensive manual annotation. These generalized representations improve transfer learning, few-shot learning, zero-shot learning, and clinical generalizability across diverse malignancies.

Integration of foundation models with continuous learning systems allows computational reasoning to evolve dynamically as new patient information becomes available, thereby strengthening adaptive diagnosis, prognostic assessment, therapeutic optimization, and disease monitoring.[15]

7.Real-Time Monitoring of Tumor Evolution

Tumor evolution is characterized by continuous genetic mutation, clonal selection, immune escape, metabolic adaptation, angiogenesis, and therapeutic resistance. Traditional episodic assessments frequently fail to capture these dynamic biological changes until clinically significant progression has already occurred.[16]

Artificial intelligence enables real-time monitoring by continuously integrating imaging studies, digital pathology, circulating tumor DNA, liquid biopsy, laboratory biomarkers, wearable physiological monitoring, and longitudinal clinical records into adaptive computational models of tumor behavior.

These continuously evolving computational representations facilitate early detection of recurrence, therapeutic resistance, metastatic dissemination, and treatment-related toxicity while enabling timely clinical intervention before irreversible disease progression develops.[17]

8.Personalized Clinical Decision Support

Continuous learning systems provide the computational foundation for intelligent real-time clinical decision-support platforms capable of integrating multimodal biomedical information into adaptive patient-centered recommendations. Radiological imaging, pathology, genomics, laboratory investigations, wearable technologies, medication history, physician documentation, and longitudinal clinical outcomes are harmonized into unified computational environments supporting precision oncology.[18]

Interactive clinical dashboards generate individualized diagnostic summaries, prognostic estimates, therapeutic recommendations, toxicity predictions, recurrence probabilities, survival forecasts, and adaptive treatment pathways while facilitating multidisciplinary collaboration among oncologists, radiologists, pathologists, surgeons, molecular biologists, and data scientists.

These intelligent systems enable clinicians to make evidence-based decisions using continuously updated biomedical knowledge while improving workflow efficiency and patient-centered care.[19]

9.Digital Twins and Adaptive Patient Models

Digital twin technology represents one of the most promising applications of real-time oncology. AI-powered digital twins integrate imaging, pathology, multi-omics, laboratory biomarkers, wearable devices, medication history, and longitudinal clinical information into continuously evolving virtual patient models capable of simulating disease progression and therapeutic response.[20]

10.Reinforcement Learning and Adaptive Therapeutic Optimization

Reinforcement learning has emerged as a powerful artificial intelligence paradigm for optimizing therapeutic decision-making in real-time oncology. Unlike conventional predictive models that generate static recommendations, reinforcement learning continuously learns from patient outcomes by evaluating the effectiveness of previous therapeutic interventions and adapting future treatment strategies accordingly.[21]

By integrating radiological imaging, digital pathology, circulating tumor DNA, laboratory biomarkers, wearable physiological monitoring, medication history, and longitudinal clinical outcomes, reinforcement learning algorithms estimate the expected benefit of alternative therapeutic pathways while balancing treatment efficacy, toxicity, quality of life, and long-term survival. These adaptive systems support personalized treatment scheduling, dose optimization, combination therapy selection, and timely modification of therapeutic regimens as tumor biology evolves.

11.Wearable Technologies and Continuous Patient Monitoring

Wearable health technologies are becoming increasingly important components of real-time oncology because they enable continuous monitoring of physiological status outside traditional healthcare environments. Smartwatches, biosensors, mobile health applications, and remote monitoring platforms provide longitudinal information regarding heart rate, physical activity, sleep patterns, respiratory function, temperature, treatment adherence, symptom burden, and patient-reported outcomes.[22]

Artificial intelligence integrates these real-world physiological measurements with radiological imaging, laboratory investigations, molecular diagnostics, and electronic health records to generate comprehensive representations of patient health. Continuous monitoring enables early identification of treatment-related toxicities, infection, functional decline, dehydration, and disease progression while facilitating timely clinical intervention and reducing avoidable hospitalizations.

12.Liquid Biopsy and Dynamic Molecular Surveillance

Liquid biopsy has transformed cancer monitoring by enabling minimally invasive assessment of tumor biology through analysis of circulating tumor DNA, circulating tumor cells, extracellular vesicles, microRNAs, and other blood-based biomarkers. Unlike conventional tissue biopsy, liquid biopsy can be repeated frequently, providing real-time insight into tumor evolution throughout treatment.[23]

Continuous learning AI systems integrate liquid biopsy findings with radiological imaging, computational pathology, genomics, transcriptomics, proteomics, laboratory biomarkers, and clinical history to model clonal evolution, detect emerging therapeutic resistance, identify minimal residual disease, and predict recurrence before radiological progression becomes evident.

These adaptive molecular surveillance systems substantially improve personalized oncology by enabling proactive modification of therapeutic strategies according to evolving tumor biology.

13.Federated Learning and Collaborative Oncology Intelligence

The effectiveness of continuous learning systems depends upon access to diverse, high-quality clinical datasets. However, concerns regarding patient privacy, regulatory compliance, and institutional data governance frequently limit centralized data sharing. Federated learning addresses these challenges by enabling artificial intelligence models to learn collaboratively from distributed healthcare datasets without transferring sensitive patient information.[24]

Individual healthcare institutions train local versions of AI models using their own patient data while sharing only model parameters or encrypted updates with a central coordinating framework. This collaborative learning strategy improves model robustness, generalizability, and fairness across diverse patient populations while preserving privacy and regulatory compliance.

Federated continuous learning is expected to become a foundational component of large-scale precision oncology networks supporting global evidence generation and equitable deployment of intelligent cancer care.

14.Explainability, Safety, and Regulatory Implementation

Successful deployment of real-time oncology systems requires more than predictive accuracy; clinicians must also understand, trust, and appropriately interpret AI-generated recommendations. Explainable artificial intelligence (XAI) techniques—including attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, and counterfactual reasoning—help reveal the biological and clinical variables contributing to computational predictions.[25]

Continuous learning systems present additional regulatory challenges because algorithms evolve after deployment. Consequently, healthcare organizations require robust monitoring frameworks capable of evaluating model performance, detecting algorithmic drift, validating updates, ensuring reproducibility, and maintaining patient safety over time.

Strong cybersecurity measures, standardized interoperability protocols, transparent governance, equitable implementation, informed consent procedures, and international regulatory collaboration will be essential for responsible adoption of continuously learning AI systems in oncology.

15.Future Perspectives

The future of real-time oncology will increasingly integrate multimodal foundation models, large language models, agentic artificial intelligence, digital twins, federated learning, reinforcement learning, spatial multi-omics, liquid biopsy, Internet of Medical Things (IoMT) technologies, edge computing, cloud-native healthcare infrastructure, and quantum computing into comprehensive intelligent oncology ecosystems.[26]

These next-generation systems will continuously assimilate molecular biology, imaging, pathology, wearable physiological monitoring, laboratory medicine, electronic health records, environmental exposures, lifestyle factors, and real-world clinical outcomes while autonomously coordinating diagnostic workflows, optimizing therapeutics, generating personalized patient education, and supporting continuous evidence synthesis.

Such computational ecosystems are expected to transform oncology from episodic disease management toward predictive, preventive, adaptive, and continuously personalized cancer care.

16.Discussion

Artificial intelligence for real-time oncology represents a fundamental paradigm shift from static predictive models toward continuously evolving computational systems capable of adapting alongside changing patient biology and advancing clinical knowledge. Unlike conventional decision-support tools trained on historical datasets, continuous learning systems integrate multimodal biomedical information throughout the patient journey, generating dynamic recommendations that reflect current disease status rather than historical snapshots.[27]

Applications spanning adaptive therapeutics, liquid biopsy surveillance, wearable monitoring, digital twins, federated learning, intelligent clinical decision support, and multimodal foundation models illustrate the transformative potential of continuous learning systems for precision oncology. Nevertheless, widespread clinical implementation requires rigorous validation, explainability, standardized interoperability, secure computational infrastructure, ethical governance, and sustained multidisciplinary collaboration to ensure safe, equitable, and effective deployment.

17.Conclusion

Artificial intelligence is redefining real-time oncology by enabling continuous learning systems that integrate radiological imaging, digital pathology, multi-omics, liquid biopsy, laboratory biomarkers, wearable technologies, electronic health records, and longitudinal clinical information into unified computational frameworks capable of supporting adaptive precision medicine.[28]

Advances in transformer architectures, multimodal foundation models, graph neural networks, reinforcement learning, federated learning, digital twins, agentic AI, and generative artificial intelligence are expected to further strengthen intelligent oncology ecosystems, enabling increasingly accurate diagnosis, dynamic therapeutic optimization, continuous disease monitoring, and evidence-based clinical decision-making throughout the cancer care continuum.[29]

Although important scientific, technical, ethical, regulatory, and organizational challenges remain, continued collaboration among oncologists, radiologists, pathologists, molecular biologists, biomedical engineers, computer scientists, healthcare organizations, industry partners, and regulatory agencies will accelerate responsible implementation of continuously learning AI systems. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce treatment variability, and establish a new era of truly personalized, adaptive, and real-time cancer care worldwide.[30]

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