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

Artificial Intelligence and Digital Twin Networks for Predictive and Preventive Precision Oncology

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ABSTRACT:
Precision oncology is undergoing a paradigm shift from reactive disease management toward predictive, preventive, and continuously adaptive cancer care through the convergence of artificial intelligence (AI) and digital twin technologies. Conventional oncology relies largely on episodic clinical assessments and static treatment strategies that often fail to capture the dynamic evolution of tumor biology and patient physiology. Digital twin networks, empowered by foundation AI models, multimodal transformers, graph neural networks, self-supervised learning, and generative artificial intelligence, enable the creation of continuously evolving virtual representations of patients that integrate radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, spatial biology, laboratory biomarkers, wearable technologies, electronic health records, and longitudinal clinical outcomes. These computational ecosystems support biomarker discovery, therapeutic response prediction, adaptive treatment optimization, recurrence monitoring, preventive risk assessment, intelligent clinical decision support, and systems oncology while accelerating personalized medicine. Recent advances in large language models, reinforcement learning, federated learning, retrieval-augmented generation, explainable artificial intelligence, and agentic AI have further expanded the capabilities of digital twin networks by enabling collaborative, privacy-preserving, and continuously learning computational frameworks. Despite remarkable technological progress, important challenges remain regarding multimodal data harmonization, computational scalability, interpretability, interoperability, cybersecurity, regulatory validation, ethical governance, and equitable implementation. This review provides a comprehensive overview of artificial intelligence and digital twin networks for predictive and preventive precision oncology, emphasizing computational principles, clinical applications, implementation challenges, and future perspectives for intelligent virtual oncology ecosystems.[1]

Keyword: Digital twins, Artificial intelligence, Precision oncology, Foundation models, Predictive oncology, Preventive oncology, Computational oncology, Multimodal learning, Clinical decision support, Personalized medicine.

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

1.Introduction

Cancer remains one of the most biologically complex diseases in medicine because of its continuous genetic evolution, epigenetic remodeling, immune adaptation, metabolic reprogramming, and interactions within the tumor microenvironment. Traditional oncology often relies on intermittent clinical assessments that capture isolated snapshots of disease status, limiting the ability to anticipate tumor evolution and proactively optimize therapeutic strategies.[2]

Modern oncology generates enormous quantities of heterogeneous biomedical information through radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, spatial biology, laboratory investigations, liquid biopsy, wearable biosensors, electronic health records, and patient-reported outcomes. Although each modality contributes valuable biological insight, isolated interpretation frequently fails to represent the dynamic interactions governing disease progression and treatment response.[3]

Artificial intelligence has emerged as a transformative computational technology capable of integrating these diverse biomedical datasets into unified patient-centered representations. Digital twin technology extends this capability by creating continuously evolving virtual patients synchronized with biological individuals throughout diagnosis, treatment, follow-up, and survivorship.[4]

The convergence of AI and digital twin networks is therefore redefining predictive and preventive precision oncology by enabling intelligent simulation of disease evolution, therapeutic response, and personalized clinical decision-making before major clinical events occur.[5]

2.Evolution of Digital Twins in Oncology

The concept of digital twins originated in engineering, where virtual replicas of complex systems were continuously synchronized with physical counterparts to monitor performance, predict failures, and optimize operations. Advances in computational biology, biomedical engineering, and artificial intelligence have extended this paradigm into healthcare, enabling patient-specific computational representations that evolve alongside biological processes.[6]

Early digital health systems primarily stored electronic clinical information without dynamic biological modeling. Subsequent integration of molecular biology, radiological imaging, computational pathology, wearable technologies, and real-time physiological monitoring substantially expanded computational capabilities.

Foundation AI models have further transformed digital twins through generalized multimodal representation learning, allowing integration of heterogeneous biomedical information into continuously adaptive virtual patient ecosystems capable of supporting predictive precision oncology.

Today, digital twin networks represent interconnected computational environments in which individual virtual patients contribute to collaborative clinical intelligence while preserving personalized decision-making.[7]

3.Principles of AI-Driven Digital Twin Networks

Digital twin networks differ fundamentally from conventional predictive models because they continuously integrate multimodal biomedical information into synchronized virtual representations of individual patients. Artificial intelligence serves as the computational engine responsible for learning, updating, and simulating biological behavior across molecular, cellular, tissue, organ, and patient levels.[8]

These computational ecosystems incorporate radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, liquid biopsy, wearable technologies, medication history, physician documentation, and longitudinal clinical trajectories into unified patient-specific embeddings.

Graph neural networks model interactions among molecular pathways, immune populations, signaling networks, imaging phenotypes, therapeutic targets, physiological variables, and clinical outcomes, while transformer architectures enable multimodal reasoning across complementary biomedical domains.[9]

4.Computational Architecture

Modern digital twin networks consist of interconnected computational layers responsible for multimodal data acquisition, preprocessing, representation learning, virtual patient modeling, predictive simulation, adaptive learning, and intelligent clinical decision support.[10]

The acquisition layer continuously collects radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, spatial biology, laboratory investigations, wearable physiological monitoring, liquid biopsy, medication history, and electronic health records. Advanced preprocessing pipelines normalize imaging studies, harmonize molecular datasets, encode unstructured clinical documentation using natural language processing, and synchronize temporal patient information.

Foundation AI models generate generalized multimodal embeddings representing biological state, disease progression, physiological function, and clinical trajectory. Simulation engines continuously update virtual patient models using newly acquired biomedical information while supporting individualized prediction of future disease behavior.[11]

5.Foundation AI Models for Virtual Patient Representation

Foundation AI models provide the computational backbone for digital twin networks because generalized multimodal representations enable integration of heterogeneous biomedical information across multiple organizational scales. Unlike task-specific machine learning algorithms, foundation models acquire transferable biomedical knowledge through large-scale self-supervised learning before adaptation to specialized oncology applications.[12]

Transformer architectures integrate radiological imaging, computational pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable physiological monitoring, and longitudinal clinical records into comprehensive computational embeddings representing patient-specific biology.

These generalized representations substantially improve transfer learning, robustness, multimodal reasoning, and clinical generalizability while supporting increasingly accurate virtual patient simulation throughout the cancer care continuum.[13]

6.Multimodal Biomedical Integration

Digital twin networks rely upon seamless integration of multiple complementary biomedical modalities. Radiological imaging provides anatomical and functional characterization of tumors, while digital pathology contributes microscopic tissue architecture and cellular morphology. Multi-omics technologies—including genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, microbiomics, and spatial biology—provide detailed molecular characterization of tumor biology.[14]

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

Artificial intelligence harmonizes these heterogeneous datasets using multimodal transformers, graph neural networks, biological knowledge graphs, and cross-modal attention mechanisms capable of generating unified patient-centered computational representations supporting predictive precision oncology.[15]

7.Predictive Modeling of Tumor Evolution

One of the most important functions of digital twin networks is simulation of tumor evolution under changing biological and therapeutic conditions. Artificial intelligence integrates molecular biology, imaging phenotypes, computational pathology, laboratory biomarkers, liquid biopsy, and longitudinal clinical information into adaptive computational models capable of predicting disease progression, recurrence, metastatic dissemination, immune escape, and therapeutic resistance.[16]

Unlike conventional prognostic models based on static clinical variables, digital twins continuously update predictions using newly acquired biomedical information, thereby providing clinicians with evolving forecasts reflecting current disease biology.

These predictive capabilities enable proactive therapeutic planning while supporting individualized precision medicine and early clinical intervention before irreversible disease progression develops.[17]

8.Preventive Precision Oncology

Digital twin networks extend beyond therapeutic optimization by supporting preventive oncology through individualized risk assessment and early disease surveillance. Artificial intelligence analyzes inherited genetic susceptibility, environmental exposures, lifestyle factors, molecular biomarkers, imaging phenotypes, laboratory investigations, wearable physiological monitoring, and family history to estimate future cancer risk and identify opportunities for preventive intervention.[18]

Virtual patient simulations enable evaluation of preventive strategies including screening schedules, lifestyle modification, chemoprevention, prophylactic interventions, and early diagnostic pathways while accounting for patient-specific biological characteristics.

These preventive computational frameworks shift oncology from reactive disease management toward anticipatory precision healthcare focused on reducing cancer incidence, improving early detection, and minimizing long-term disease burden.[19]

9.Digital Twin Networks for Therapeutic Optimization

Digital twin networks enable clinicians to evaluate multiple therapeutic strategies within virtual patient environments before implementation in clinical practice. Artificial intelligence simulates chemotherapy, targeted therapy, immunotherapy, endocrine therapy, radiation therapy, surgical intervention, and multimodal treatment combinations while predicting efficacy, toxicity, recurrence, and survival under alternative therapeutic scenarios.[20]

10.Continuous Learning and Adaptive Digital Twin Networks

One of the defining advantages of digital twin networks is their ability to function as continuously learning computational ecosystems that evolve alongside biological patients. Unlike conventional predictive algorithms that remain static after deployment, artificial intelligence continuously incorporates newly acquired radiological imaging, digital pathology, liquid biopsy, laboratory biomarkers, wearable physiological monitoring, medication history, patient-reported outcomes, and longitudinal clinical records into adaptive virtual patient models.[21]

Continual learning algorithms enable digital twins to update predictions regarding disease progression, therapeutic response, treatment-related toxicity, recurrence, metastatic dissemination, and survival without losing previously acquired biomedical knowledge. Reinforcement learning further strengthens therapeutic optimization by evaluating the outcomes of prior clinical decisions and refining future recommendations.

These adaptive computational ecosystems provide real-time clinical intelligence while maintaining synchronization between virtual and biological patients throughout diagnosis, treatment, follow-up, and survivorship.

11.Digital Twin Networks for Precision Immuno-Oncology

The complexity of tumor–immune interactions makes immunotherapy particularly well suited for digital twin modeling. Foundation AI models integrate computational pathology, spatial transcriptomics, immunomics, radiomics, cytokine profiles, laboratory biomarkers, and longitudinal clinical outcomes into virtual immune ecosystems capable of simulating immune activation, immune escape, stromal remodeling, angiogenesis, and therapeutic response.[22]

Graph neural networks model communication among malignant cells, cytotoxic lymphocytes, macrophages, dendritic cells, fibroblasts, endothelial cells, and extracellular matrix components, enabling comprehensive simulation of the tumor immune microenvironment.

These computational immune twins improve prediction of responsiveness to immune checkpoint inhibitors, adoptive cellular therapies, cancer vaccines, bispecific antibodies, and combination immunotherapeutic strategies while supporting individualized precision immuno-oncology.

12.Collaborative Digital Twin Networks

The evolution of digital twin technology increasingly emphasizes collaborative virtual ecosystems rather than isolated patient models. Federated learning enables multiple healthcare institutions to contribute computational knowledge while preserving patient privacy, creating interconnected digital twin networks capable of learning from geographically distributed patient populations.[23]

Foundation AI models trained across international oncology centers integrate multimodal biomedical information representing diverse imaging platforms, molecular technologies, treatment protocols, and patient demographics into globally optimized computational frameworks.

These collaborative digital twin networks substantially improve model robustness, generalizability, and equity while supporting international precision oncology research and privacy-preserving artificial intelligence.

13.Intelligent Clinical Decision Support

Digital twin networks provide the computational foundation for next-generation clinical decision-support systems capable of integrating heterogeneous biomedical information into comprehensive patient-centered recommendations. Radiological imaging, computational pathology, molecular diagnostics, laboratory investigations, medication history, wearable technologies, physician documentation, and evidence-based treatment guidelines are harmonized into unified digital environments supporting multidisciplinary oncology care.[24]

Interactive clinical dashboards generate individualized diagnostic summaries, virtual patient simulations, therapeutic recommendations, toxicity estimates, recurrence probabilities, survival forecasts, and adaptive treatment pathways while facilitating collaboration among oncologists, radiologists, pathologists, surgeons, molecular biologists, pharmacists, and computational scientists.

These intelligent clinical ecosystems improve workflow efficiency, strengthen multidisciplinary communication, reduce information fragmentation, and promote evidence-based precision medicine.

14.Explainability, Validation, and Ethical Governance

Despite remarkable advances in AI-driven digital twin networks, successful clinical implementation requires transparency, interpretability, reproducibility, and rigorous scientific validation. Explainable artificial intelligence (XAI) enables clinicians to understand computational reasoning through attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, and counterfactual explanations identifying the imaging, molecular, physiological, and clinical variables contributing to AI-generated predictions.[25]

Clinical deployment also requires standardized multimodal datasets, interoperable computational infrastructure, prospective multicenter validation, continuous monitoring for algorithmic bias, cybersecurity safeguards, external benchmarking, and compliance with evolving international regulatory frameworks governing AI-enabled healthcare technologies.

Responsible implementation further depends upon protection of patient privacy, informed consent, equitable access, transparency, accountability, and continuous post-deployment monitoring to ensure trustworthy integration of digital twin technologies into routine oncology practice.

15.Future Perspectives

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

These next-generation computational platforms will continuously integrate molecular biology, imaging, pathology, laboratory medicine, wearable physiological monitoring, environmental exposures, electronic health records, and real-world clinical outcomes while autonomously coordinating diagnostic workflows, optimizing therapeutic strategies, supporting adaptive clinical trials, generating personalized patient communication, and continuously synthesizing biomedical evidence.

Such intelligent digital twin networks are expected to transform oncology from reactive disease management toward predictive, preventive, adaptive, and continuously personalized healthcare.

16.Discussion

Artificial intelligence-driven digital twin networks represent one of the most transformative paradigm shifts in precision oncology by integrating multimodal biomedical information into continuously evolving virtual patient ecosystems capable of modeling tumor biology, therapeutic response, disease progression, and preventive interventions. Unlike conventional predictive models, digital twins simulate dynamic biological processes across molecular, cellular, tissue, organ, and patient levels while supporting individualized therapeutic optimization and evidence-based clinical decision-making.[27]

Applications spanning computational pathology, radiomics, multi-omics integration, immunotherapy, continuous learning, federated collaboration, intelligent clinical decision support, and preventive oncology demonstrate the extraordinary translational potential of digital twin technologies. Nevertheless, successful implementation requires continued advances in multimodal data harmonization, explainable artificial intelligence, interoperability, computational infrastructure, cybersecurity, regulatory science, ethical governance, and multidisciplinary collaboration.

DOI: https://doi.org/10.65477/ijrems.v1.i7.07

As biomedical datasets continue to expand in scale and complexity, interconnected digital twin networks are expected to become a foundational technology supporting next-generation predictive precision oncology.

17.Conclusion

Artificial intelligence and digital twin networks are redefining predictive and preventive precision oncology by integrating radiological imaging, digital pathology, multi-omics, laboratory biomarkers, wearable technologies, electronic health records, and longitudinal clinical intelligence into unified computational frameworks capable of supporting personalized cancer care throughout the disease continuum.[28]

Advances in foundation AI models, transformer architectures, graph neural networks, multimodal learning, self-supervised learning, federated learning, reinforcement learning, large language models, agentic AI, and generative artificial intelligence are expected to further strengthen virtual oncology ecosystems, enabling increasingly accurate prediction of tumor evolution, adaptive therapeutic optimization, continuous disease monitoring, preventive intervention, and evidence-based clinical decision-making.[29]

Although important scientific, technical, ethical, regulatory, and implementation challenges remain, sustained collaboration among oncologists, radiologists, pathologists, molecular biologists, biomedical engineers, computer scientists, healthcare organizations, policymakers, and regulatory agencies will accelerate responsible implementation of digital twin networks. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce cancer burden through preventive strategies, and establish a new era of intelligent, predictive, and continuously learning precision oncology worldwide.[30]

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