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Artificial Intelligence in Pediatric Oncology: Toward Personalized Childhood Cancer Care

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ABSTRACT

Background:
Pediatric oncology has witnessed remarkable advances over the past several decades, resulting in significant improvements in survival for many childhood cancers. Nevertheless, cancer remains one of the leading causes of disease-related mortality among children worldwide, and survivors frequently experience long-term treatment-related complications affecting physical, cognitive, endocrine, cardiovascular, and psychosocial health. The extraordinary biological diversity of childhood malignancies, together with age-dependent physiology, genetic predisposition, developmental considerations, and variable therapeutic responses, necessitates highly individualized approaches to diagnosis and treatment. Recent developments in artificial intelligence (AI), computational oncology, multimodal data integration, and precision medicine have introduced transformative opportunities for personalized childhood cancer care. Artificial intelligence integrates radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, laboratory investigations, electronic health records, physiological monitoring, and longitudinal clinical information into comprehensive computational models capable of supporting diagnosis, molecular classification, prognostic prediction, treatment optimization, toxicity assessment, recurrence monitoring, and survivorship management. Advances in deep learning, transformer architectures, foundation models, graph neural networks, reinforcement learning, and explainable artificial intelligence have further accelerated clinical implementation across pediatric oncology. Despite remarkable progress, challenges remain regarding limited pediatric datasets, data interoperability, algorithmic fairness, ethical governance, cybersecurity, regulatory validation, and equitable healthcare access. This review provides a comprehensive overview of artificial intelligence in pediatric oncology, highlighting computational foundations, current clinical applications, emerging innovations, implementation challenges, and future perspectives toward personalized childhood cancer care.[1]

Keywords: *Artificial intelligence, Pediatric oncology, Childhood cancer, Precision medicine, Machine learning, Deep learning, Computational pathology, Medical imaging, Personalized medicine, Clinical decision support.*

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Introduction

Childhood cancers differ fundamentally from adult malignancies in their biological origin, genomic landscape, developmental context, and therapeutic management. Leukemias, brain tumors, lymphomas, neuroblastoma, Wilms tumor, sarcomas, retinoblastoma, and germ cell tumors collectively represent the most common pediatric malignancies. Although substantial improvements in diagnosis and treatment have increased survival rates in many high-income countries, childhood cancer continues to impose significant global morbidity and mortality, particularly in resource-limited healthcare systems.[2]

Unlike adult cancers, pediatric malignancies often arise from developmental abnormalities rather than cumulative environmental exposure. Children exhibit unique physiological characteristics, rapidly changing organ function, ongoing growth, immune maturation, and developmental processes that significantly influence disease progression, treatment response, drug metabolism, and long-term survivorship. Consequently, therapeutic decisions require highly individualized clinical assessment that extends beyond conventional population-based treatment strategies.[3]

Modern pediatric oncology generates enormous quantities of heterogeneous biomedical information through radiological imaging, digital pathology, genomic sequencing, transcriptomics, laboratory investigations, minimal residual disease monitoring, physiological monitoring, electronic health records, and long-term survivorship data. Integrating these diverse datasets into clinically meaningful treatment recommendations represents one of the greatest challenges in contemporary pediatric cancer care.[4]

Artificial intelligence has emerged as one of the most transformative technologies capable of addressing this complexity. Machine learning algorithms identify hidden relationships among clinical variables, deep learning models analyze imaging and pathology, transformer architectures process clinical documentation, and multimodal learning integrates heterogeneous biomedical information into unified computational representations supporting individualized patient care.[5]

Artificial intelligence-driven pediatric oncology now enables personalized diagnosis, molecular classification, therapeutic optimization, toxicity prediction, recurrence monitoring, and survivorship planning while complementing physician expertise and multidisciplinary clinical decision-making.[6]

2. Evolution of Artificial Intelligence in Pediatric Oncology

The practice of pediatric oncology has evolved substantially through advances in molecular biology, medical imaging, targeted therapeutics, supportive care, and precision medicine. Historically, treatment decisions relied primarily on tumor histology, anatomical location, disease stage, and standardized chemotherapy protocols. Although these approaches substantially improved survival, they often failed to account for biological heterogeneity among pediatric tumors.[7]

Advances in molecular genetics introduced a deeper understanding of childhood cancers through identification of chromosomal abnormalities, inherited cancer predisposition syndromes, gene fusions, epigenetic regulation, and molecular signaling pathways. High-throughput genomic sequencing further enabled comprehensive molecular characterization of pediatric malignancies, facilitating development of individualized therapeutic strategies.[8]

Artificial intelligence accelerated this transition by integrating molecular biology with radiological imaging, digital pathology, laboratory investigations, and longitudinal clinical information into computational models capable of supporting personalized diagnosis and treatment planning. Machine learning algorithms identify complex biological relationships that remain difficult to recognize using conventional statistical methods.[9]

Recent developments in multimodal artificial intelligence, transformer architectures, foundation models, and computational oncology have further expanded pediatric precision medicine through comprehensive integration of genomic, imaging, physiological, and clinical information into continuously evolving patient-specific computational representations.[10]

Today, artificial intelligence has become a central component of next-generation pediatric oncology, supporting individualized clinical care from diagnosis through long-term survivorship.[11]

3. Computational Foundations of Artificial Intelligence in Pediatric Oncology

Artificial intelligence-driven pediatric oncology relies on multiple complementary computational methodologies capable of analyzing heterogeneous biomedical information across molecular, cellular, anatomical, physiological, and clinical domains. Rather than functioning as isolated predictive algorithms, modern pediatric oncology integrates several artificial intelligence techniques operating simultaneously to support individualized clinical decision-making.[12]

Traditional machine learning algorithms—including logistic regression, support vector machines, decision trees, random forests, and gradient boosting methods—initially demonstrated considerable success in predicting treatment response, recurrence, toxicity, and survival using structured clinical datasets. Although highly effective, these approaches generally required manually engineered features and limited biological representation.[13]

Deep learning significantly expanded computational capabilities by automatically extracting hierarchical features from medical imaging, digital pathology, genomic information, and physiological signals. Convolutional neural networks revolutionized interpretation of radiological imaging and histopathology, while recurrent neural networks enabled temporal modeling of longitudinal clinical information.[14]

Transformer architectures have recently become central to pediatric precision oncology because self-attention mechanisms efficiently integrate imaging findings, genomic sequencing, pathology reports, laboratory biomarkers, physician documentation, and electronic health records into unified patient representations supporting individualized therapeutic recommendations.[15]

Foundation models pretrained on massive biomedical datasets further enhance scalability through transfer learning, allowing adaptation across multiple pediatric malignancies while reducing dependence on manually annotated datasets and improving generalizability across healthcare institutions.[16]

4. Multimodal Data Integration in Childhood Cancer

Precision pediatric oncology depends fundamentally upon integration of heterogeneous biomedical information into comprehensive computational frameworks. Childhood cancers arise through complex interactions among developmental biology, inherited genetics, somatic mutations, immune responses, environmental influences, treatment exposure, and physiological maturation. Therefore, isolated datasets rarely capture the full biological complexity of pediatric malignancies.[17]

Radiological imaging contributes detailed anatomical and functional information regarding tumor morphology, local invasion, metastatic spread, vascularity, and treatment response. Digital pathology provides microscopic evaluation of tumor architecture, cellular differentiation, mitotic activity, immune infiltration, stromal remodeling, angiogenesis, and molecular characteristics. Genomic sequencing identifies clinically relevant mutations, chromosomal rearrangements, gene fusions, epigenetic alterations, and inherited cancer predisposition syndromes associated with diagnosis and therapeutic response.[18]

Clinical information—including laboratory investigations, medication history, developmental milestones, family history, nutritional status, physiological monitoring, treatment records, and long-term follow-up—adds essential context supporting individualized clinical decision-making. Artificial intelligence harmonizes these heterogeneous datasets through multimodal representation learning capable of identifying hidden biological relationships beyond conventional statistical analysis.[19]

Continuous incorporation of newly acquired patient information enables adaptive precision medicine throughout diagnosis, treatment, remission, relapse, and survivorship.[20]

5. Artificial Intelligence in Pediatric Leukemia

Leukemia represents the most common childhood malignancy worldwide, with acute lymphoblastic leukemia accounting for the majority of pediatric cases. Despite remarkable improvements in survival, treatment remains highly individualized because therapeutic response varies substantially according to molecular subtype, minimal residual disease status, cytogenetic abnormalities, and patient-specific biological characteristics.[21]

Artificial intelligence integrates peripheral blood analysis, bone marrow pathology, flow cytometry, genomic sequencing, cytogenetics, laboratory investigations, minimal residual disease measurements, and electronic health records into comprehensive computational models supporting diagnosis, molecular classification, risk stratification, and individualized treatment planning.[22]

Machine learning algorithms predict chemotherapy response, relapse probability, treatment-related toxicity, infection risk, and long-term survival while supporting individualized therapeutic intensity. Continuous analysis of minimal residual disease further enables early identification of treatment resistance and optimization of subsequent therapeutic interventions.[23]

6. Artificial Intelligence in Pediatric Brain Tumors

Brain tumors represent the leading cause of cancer-related mortality among children and encompass biologically diverse malignancies requiring highly individualized diagnosis and treatment. Artificial intelligence has significantly enhanced pediatric neuro-oncology through advanced analysis of magnetic resonance imaging, digital pathology, molecular diagnostics, and clinical information.

Deep learning algorithms automatically detect intracranial tumors, segment anatomical structures, estimate tumor volume, characterize imaging phenotypes, predict molecular subtypes, and assess treatment response with remarkable accuracy. Radiomics further extracts quantitative imaging biomarkers describing tumor heterogeneity, vascularity, texture, and metabolic activity, substantially improving individualized prognostic prediction.[24]

Artificial intelligence also integrates histopathology, genomic sequencing, methylation profiling, and transcriptomics to support molecular classification of medulloblastoma, glioma, ependymoma, atypical teratoid/rhabdoid tumor, and other pediatric brain tumors, thereby facilitating precision therapeutic selection and long-term outcome prediction.[25]

7. Artificial Intelligence in Pediatric Solid Tumors

Artificial intelligence increasingly supports management of pediatric solid tumors including neuroblastoma, Wilms tumor, osteosarcoma, Ewing sarcoma, rhabdomyosarcoma, hepatoblastoma, and retinoblastoma. These malignancies exhibit substantial biological diversity requiring integration of imaging, pathology, molecular biology, and clinical information for optimal management.[26]

Machine learning algorithms analyze computed tomography, magnetic resonance imaging, positron emission tomography, digital pathology, laboratory biomarkers, genomic sequencing, and treatment history to support early diagnosis, tumor staging, molecular classification, therapeutic response prediction, and recurrence monitoring. Deep learning further enables automated tumor segmentation, radiomics analysis, computational pathology, and individualized prognostic assessment.[27]

Artificial intelligence assists multidisciplinary pediatric oncology teams by comparing surgical approaches, chemotherapy regimens, radiation therapy protocols, targeted therapies, and immunotherapeutic strategies according to each child's biological characteristics while minimizing treatment-related toxicity and preserving long-term quality of life.[28]

8. Computational Pathology and Molecular Diagnostics

Computational pathology has become one of the most important applications of artificial intelligence in pediatric oncology. Whole-slide imaging enables the digitization of histopathological specimens at ultra-high resolution, allowing deep learning algorithms to evaluate millions of microscopic image regions simultaneously. These computational approaches improve diagnostic accuracy while reducing interobserver variability among pathologists.[29]

Transformer-based pathology models automatically identify histomorphological features associated with tumor subtype, cellular differentiation, mitotic activity, necrosis, angiogenesis, stromal remodeling, immune infiltration, and metastatic potential. These microscopic biomarkers significantly enhance diagnosis, prognostic prediction, and individualized therapeutic planning across childhood malignancies.[30]

Artificial intelligence also enables prediction of molecular biomarkers directly from routine histopathological images. Deep learning algorithms have demonstrated the ability to infer chromosomal abnormalities, gene fusions, mutation profiles, methylation patterns, and clinically relevant molecular subtypes from tissue morphology, potentially reducing dependence on expensive molecular testing while accelerating precision pediatric oncology workflows.[31]

9. Radiomics and Radiogenomics in Childhood Cancer

Radiomics has substantially expanded the clinical value of pediatric medical imaging by extracting hundreds of quantitative imaging biomarkers describing tumor morphology, texture, vascularity, metabolism, heterogeneity, and spatial organization. Unlike conventional visual interpretation, radiomics provides objective quantitative information capable of supporting highly individualized clinical decision-making.[32]

Radiogenomics further integrates these imaging biomarkers with genomic sequencing, transcriptomics, proteomics, and molecular diagnostics to establish relationships between radiological phenotypes and underlying tumor biology. Artificial intelligence identifies imaging signatures associated with chromosomal alterations, gene expression profiles, therapeutic sensitivity, and prognosis across pediatric malignancies.

Integration of radiogenomics into precision pediatric oncology enables continuous non-invasive monitoring of tumor evolution throughout treatment. Serial imaging examinations provide updated information regarding disease progression, therapeutic response, and emerging resistance mechanisms without requiring repeated invasive tissue biopsies.[33]

10. Personalized Therapeutic Planning

Artificial intelligence significantly enhances personalized treatment planning by integrating multidimensional biomedical information into computational models capable of simulating individualized therapeutic response. Rather than relying exclusively on standardized pediatric treatment protocols, clinicians can evaluate multiple therapeutic strategies according to each child's biological characteristics and clinical condition.

Machine learning algorithms estimate chemotherapy sensitivity, radiation response, targeted therapy efficacy, immunotherapy benefit, treatment-related toxicity, relapse probability, progression-free survival, and long-term survival. These predictive models support individualized treatment selection while minimizing unnecessary toxicity and preserving normal growth and development.[34]

Continuous incorporation of newly acquired imaging findings, laboratory biomarkers, genomic information, and treatment response enables adaptive therapeutic optimization throughout the child's cancer journey, recognizing that tumor biology and patient physiology evolve continuously during treatment.[35]

11. Artificial Intelligence in Immunotherapy and Cellular Therapy

Recent advances in immunotherapy have created new opportunities for treating pediatric malignancies, particularly relapsed leukemia, lymphoma, and selected solid tumors. Nevertheless, predicting which children will benefit from immunotherapy remains a major challenge because of substantial biological variability among patients.

Artificial intelligence integrates genomic alterations, immune-cell composition, cytokine signaling, digital pathology, radiological imaging, tumor mutational burden, laboratory biomarkers, and clinical characteristics into predictive models capable of estimating individualized immunotherapy response before treatment initiation.[36]

Machine learning algorithms quantify tumor-infiltrating lymphocytes, immune checkpoint expression, inflammatory signaling pathways, stromal remodeling, and immune-cell spatial organization. These computational insights assist clinicians in optimizing immune checkpoint inhibitors, CAR-T cell therapy, cancer vaccines, bispecific antibodies, and combination immunotherapeutic strategies while minimizing immune-related toxicities.[37]

12. Artificial Intelligence in Drug Discovery and Clinical Trials

Development of new therapies for childhood cancers remains particularly challenging because of the relatively small number of pediatric patients and the biological rarity of many childhood malignancies. Artificial intelligence significantly accelerates pediatric drug discovery by integrating systems biology, pharmacology, molecular chemistry, genomic sequencing, and disease-specific biological pathways into computational models.

Machine learning algorithms identify novel therapeutic targets, predict drug-target interactions, estimate pharmacokinetic and pharmacodynamic properties, optimize dosing strategies, and evaluate toxicity before laboratory or clinical testing. These virtual experiments reduce research costs while improving selection of promising therapeutic candidates.[38]

Artificial intelligence also improves pediatric clinical trial design by identifying patients most likely to benefit from investigational therapies, optimizing participant stratification, reducing trial variability, and increasing statistical efficiency. Adaptive trial designs supported by computational prediction may further accelerate development and regulatory approval of innovative pediatric cancer treatments.[39]

13. Explainable Artificial Intelligence and Trustworthy Pediatric Oncology

Clinical implementation of artificial intelligence in pediatric oncology requires transparent and interpretable computational systems that clinicians and families can understand and trust. Explainable artificial intelligence (XAI) addresses this need by providing meaningful explanations for diagnostic and therapeutic predictions rather than functioning as opaque "black-box" algorithms.

Saliency maps identify radiological or pathological image regions contributing most strongly to diagnostic predictions, while SHAP (Shapley Additive Explanations) values estimate the contribution of laboratory biomarkers, genomic alterations, clinical variables, and imaging features to individualized predictions. Counterfactual explanations further demonstrate how modifications in patient characteristics may influence predicted treatment outcomes.[40]

Transparent artificial intelligence facilitates communication among pediatric oncologists, radiologists, pathologists, surgeons, pharmacists, nurses, genetic counselors, patients, and families while improving physician confidence, supporting regulatory approval, reducing algorithmic bias, and promoting responsible implementation of intelligent healthcare technologies.[41]

14. Federated Learning, Privacy Protection, and Ethical Considerations

Large-scale pediatric oncology research requires collaboration among children's hospitals, cancer centers, genomic laboratories, imaging facilities, and international research networks. However, direct sharing of sensitive pediatric patient information raises significant concerns regarding privacy, confidentiality, cybersecurity, and ethical governance.

Federated learning enables collaborative artificial intelligence development without transferring raw patient data among participating institutions. Individual hospitals train AI algorithms locally using their own clinical datasets, while only encrypted model parameters are securely aggregated into improved global models. This decentralized learning strategy preserves patient privacy while enabling continuous improvement across geographically diverse pediatric populations.[42]

Additional privacy-preserving technologies—including differential privacy, secure multi-party computation, homomorphic encryption, blockchain-based audit systems, and encrypted cloud computing—further strengthen cybersecurity within pediatric oncology ecosystems. Robust authentication mechanisms, secure communication protocols, continuous threat monitoring, and comprehensive ethical governance remain essential because artificial intelligence systems process highly sensitive clinical, genetic, and developmental information throughout childhood cancer care.[43]

15. Digital Biomarkers and Continuous Monitoring in Pediatric Oncology

The rapid advancement of wearable technologies, biosensors, mobile health applications, and remote physiological monitoring has significantly expanded the role of artificial intelligence in pediatric oncology. Unlike conventional follow-up based on scheduled hospital visits, continuous monitoring enables real-time assessment of physiological changes throughout treatment and survivorship. Digital biomarkers derived from heart rate, respiratory rate, oxygen saturation, physical activity, sleep quality, body temperature, nutritional status, and patient-reported symptoms provide valuable information regarding treatment tolerance, disease progression, and recovery.[44]

Artificial intelligence continuously integrates these physiological measurements with laboratory investigations, imaging findings, medication history, and electronic health records to identify early signs of infection, treatment-related toxicity, relapse, organ dysfunction, and functional decline. Early recognition of clinical deterioration enables timely intervention, reducing hospitalization, improving supportive care, and enhancing long-term outcomes.

Continuous monitoring also improves family-centered care by allowing healthcare providers to assess children in their home environment while reducing unnecessary hospital visits. Integration of wearable technologies with intelligent clinical decision-support systems therefore extends personalized pediatric oncology beyond traditional hospital settings.[45]

16. Artificial Intelligence in Survivorship and Long-Term Follow-Up

Advances in pediatric oncology have resulted in a growing population of long-term childhood cancer survivors. However, many survivors experience chronic complications including cardiotoxicity, endocrine disorders, infertility, neurocognitive impairment, secondary malignancies, pulmonary dysfunction, renal impairment, psychosocial challenges, and reduced quality of life.

Artificial intelligence supports personalized survivorship care by integrating treatment history, genomic susceptibility, imaging findings, laboratory biomarkers, developmental milestones, educational performance, lifestyle factors, and longitudinal clinical information into predictive computational models. Machine learning estimates individualized risk of late treatment-related complications while recommending personalized surveillance schedules and preventive interventions.[46]

These predictive systems enable clinicians to identify high-risk survivors who require intensified follow-up while avoiding unnecessary investigations for lower-risk individuals. Personalized survivorship planning improves quality of life, supports healthy childhood development, and reduces long-term healthcare costs through evidence-based preventive care.[47]

17. Emerging Innovations in Artificial Intelligence for Childhood Cancer

Rapid advances in computational medicine continue to expand the capabilities of artificial intelligence within pediatric oncology. Foundation models trained on multimodal biomedical datasets are expected to improve prediction accuracy across diverse childhood malignancies while requiring substantially less task-specific retraining.

Generative artificial intelligence has demonstrated growing potential for biomarker discovery, therapeutic target identification, molecular design, synthetic biomedical data generation, clinical documentation, scientific hypothesis generation, and educational support for healthcare professionals. Reinforcement learning algorithms further optimize adaptive treatment strategies by continuously learning from patient outcomes and refining therapeutic recommendations throughout disease progression.[48]

Graph neural networks increasingly model complex biological interactions among genes, proteins, immune cells, developmental pathways, signaling networks, and tumor microenvironment components. These computational approaches improve understanding of childhood cancer biology while facilitating discovery of novel therapeutic opportunities and personalized treatment strategies.[49]

18. Integrated Artificial Intelligence Ecosystems in Pediatric Oncology

Future pediatric oncology will increasingly operate within intelligent healthcare ecosystems integrating radiology, pathology, genomics, molecular diagnostics, laboratory medicine, surgery, radiation oncology, pharmacy, rehabilitation, telemedicine, and electronic health records into unified computational platforms.

Artificial intelligence functions as the computational foundation connecting these diverse healthcare components through continuous multimodal learning and real-time clinical decision support. Such integrated ecosystems facilitate communication among pediatric oncologists, radiologists, pathologists, surgeons, pharmacists, nurses, rehabilitation specialists, psychologists, genetic counselors, patients, and families while improving treatment coordination and patient-centered care.[50]

Cloud computing, edge computing, blockchain technology, Internet of Medical Things (IoMT), secure interoperability standards, and high-performance computational infrastructure will further enhance scalability, accessibility, computational efficiency, and secure information exchange across future pediatric oncology networks.[51]

19. Future Perspectives

The future of pediatric oncology is increasingly centered on individualized computational medicine capable of integrating molecular biology, radiological imaging, computational pathology, genomics, physiological monitoring, wearable technologies, developmental biology, and longitudinal clinical information into adaptive patient-specific healthcare systems.

Future research should prioritize large multicenter prospective studies evaluating real-world clinical implementation of artificial intelligence across diverse pediatric healthcare settings. Standardization of imaging protocols, molecular diagnostics, pathology workflows, interoperability standards, explainability methodologies, validation frameworks, and regulatory pathways will be essential for widespread clinical adoption.[52]

International collaboration among pediatric oncologists, radiologists, pathologists, biomedical engineers, computer scientists, molecular biologists, regulatory agencies, healthcare organizations, and patient advocacy groups will accelerate development of trustworthy, scalable, and equitable artificial intelligence platforms capable of supporting routine childhood cancer care worldwide.[53]

20. Discussion

Artificial intelligence has become one of the most significant technological advances in pediatric oncology by enabling comprehensive integration of imaging, pathology, genomics, laboratory investigations, physiological monitoring, electronic health records, wearable technologies, and developmental information into unified computational frameworks.

Applications across leukemia, brain tumors, neuroblastoma, Wilms tumor, sarcomas, retinoblastoma, and other childhood malignancies demonstrate the broad clinical utility of artificial intelligence in improving diagnosis, molecular classification, therapeutic selection, toxicity prediction, immunotherapy guidance, survivorship planning, and multidisciplinary clinical decision-making. Rather than replacing clinicians, artificial intelligence functions as an intelligent clinical partner that enhances evidence-based care while preserving physician expertise and compassionate family-centered medicine.[54]

Despite these substantial advances, important challenges remain. Limited pediatric datasets, rare disease prevalence, algorithmic bias, interoperability barriers, computational complexity, cybersecurity concerns, ethical governance, regulatory approval, healthcare disparities, and clinician acceptance continue to represent significant obstacles. Addressing these challenges will require rigorous prospective validation, transparent governance, multidisciplinary collaboration, and internationally harmonized standards to ensure safe, equitable, and responsible implementation of artificial intelligence in pediatric oncology.[55]

21. Conclusion

Artificial intelligence is transforming pediatric oncology by enabling precision medicine through comprehensive integration of multimodal biomedical information into individualized clinical decision-making. By combining radiology, digital pathology, genomics, molecular diagnostics, laboratory investigations, physiological monitoring, wearable technologies, and electronic health records, artificial intelligence supports personalized diagnosis, therapeutic optimization, toxicity prediction, recurrence monitoring, and long-term survivorship care.[56]

Continued advances in foundation models, explainable artificial intelligence, federated learning, multimodal learning, graph neural networks, reinforcement learning, and generative artificial intelligence are expected to further improve diagnostic accuracy, computational efficiency, scalability, interpretability, and accessibility across pediatric oncology.[57]

Although significant scientific, technical, ethical, and regulatory challenges remain, ongoing interdisciplinary research continues to accelerate translation of artificial intelligence into routine childhood cancer care. Through predictive analytics, individualized treatment planning, continuous learning, and adaptive clinical decision support, artificial intelligence has the potential to improve survival, reduce treatment-related complications, enhance quality of life, and establish the foundation for the next generation of personalized pediatric oncology worldwide.[58]

Future integration of artificial intelligence with digital biomarkers, computational modeling, precision therapeutics, real-time monitoring, and collaborative international research networks is expected to transform childhood cancer care into a continuously learning healthcare ecosystem capable of delivering safer, more effective, and truly individualized treatment for every child diagnosed with cancer.[59]

As global collaboration, technological innovation, and clinical validation continue to advance, artificial intelligence will play an increasingly central role in reducing disparities in pediatric cancer care, accelerating therapeutic discoveries, optimizing survivorship outcomes, and ultimately improving the lives of children and families affected by cancer around the world.[60]

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