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ADAPTIVE FOUNDATION MODELS IN ONCOLOGY: CONTINUOUS LEARNING FOR PERSONALIZED CANCER MANAGEMENT

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Abstract: Artificial intelligence (AI) is transforming oncology from a static decision-support technology into a continuously adaptive computational ecosystem capable of learning from evolving biomedical knowledge and patient-specific clinical trajectories. Conventional machine learning algorithms remain fixed after deployment and often struggle to accommodate the dynamic nature of tumor evolution, therapeutic resistance, changing clinical guidelines, and rapidly expanding biomedical evidence. Adaptive foundation models overcome these limitations through large-scale self-supervised learning, continual learning, multimodal transformer architectures, graph neural networks, reinforcement learning, and generative AI, enabling continuous refinement of predictive performance throughout the cancer care continuum. These intelligent computational systems integrate radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory biomarkers, liquid biopsy, wearable physiological monitoring, electronic health records, patient-reported outcomes, and longitudinal clinical data into unified patient-specific representations. Adaptive foundation models support precision diagnosis, biomarker discovery, prognostic prediction, therapeutic optimization, immunotherapy selection, digital twin simulation, intelligent clinical decision support, and personalized survivorship management while continuously incorporating new biomedical evidence. Emerging technologies including multimodal large language models, federated learning, retrieval-augmented generation, explainable artificial intelligence, and agentic AI further strengthen adaptive computational oncology by enabling collaborative, privacy-preserving, and continuously evolving precision medicine. Despite remarkable technological progress, important scientific, technical, ethical, and regulatory challenges remain regarding multimodal data harmonization, computational scalability, interpretability, interoperability, cybersecurity, clinical validation, and equitable implementation. This review provides a comprehensive overview of adaptive foundation models in oncology, emphasizing continuous learning as a transformative paradigm for personalized cancer management.[1]

Keywords: *Adaptive foundation models, Artificial intelligence, Precision oncology, Continuous learning, Personalized medicine, Computational oncology, Digital twins, Multimodal learning, Clinical decision support, Cancer intelligence.*

1. Introduction

Cancer is a biologically dynamic disease characterized by continuous genomic evolution, epigenetic remodeling, immune adaptation, metabolic reprogramming, tissue remodeling, angiogenesis, and complex interactions between malignant cells and the tumor microenvironment. These biological processes evolve throughout diagnosis, treatment, recurrence, metastasis, and survivorship, requiring computational systems capable of adapting alongside changing patient biology.[2]

Traditional artificial intelligence models are typically trained once using historical datasets before deployment into clinical environments. Although these models often achieve high predictive accuracy, their inability to continuously incorporate emerging biomedical knowledge, evolving clinical guidelines, and newly acquired patient information limits long-term clinical utility in precision oncology.[3]

Recent advances in foundation AI models, continual learning, multimodal transformers, graph neural networks, and digital health technologies have established adaptive computational frameworks capable of continuously updating biomedical knowledge while preserving previously acquired information. These intelligent systems integrate heterogeneous biomedical data across the entire patient journey, enabling increasingly personalized cancer management.[4]

The emergence of adaptive foundation models therefore represents a major paradigm shift from static predictive algorithms toward continuously evolving computational ecosystems supporting lifelong precision oncology.[5]

2. Evolution of Adaptive Artificial Intelligence in Oncology

Early artificial intelligence applications in oncology primarily relied on statistical learning algorithms and task-specific machine learning models developed for isolated diagnostic or prognostic applications. Although these systems demonstrated promising performance, they frequently required retraining when confronted with new clinical evidence, evolving treatment protocols, or changing patient populations.[6]

Deep learning substantially expanded computational capabilities through automated feature extraction from radiological imaging, digital pathology, genomic sequencing, and electronic health records. Transformer architectures subsequently revolutionized biomedical artificial intelligence by enabling generalized representation learning across heterogeneous data modalities.

Foundation AI models have further transformed computational oncology by acquiring transferable biomedical knowledge through large-scale self-supervised learning. Integration of continual learning, reinforcement learning, multimodal reasoning, digital twins, and federated learning has now established adaptive computational ecosystems capable of continuously evolving alongside biomedical knowledge and patient care.

These advances collectively define a new generation of intelligent oncology systems emphasizing adaptability rather than static prediction.[7]

3. Principles of Adaptive Foundation Models

Adaptive foundation models differ fundamentally from conventional machine learning algorithms because they continuously update computational knowledge using newly acquired biomedical information while preserving previously learned representations. Rather than treating learning as a one-time training process, adaptive models maintain evolving computational understanding throughout deployment.[8]

Foundation AI models integrate radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable physiological monitoring, physician documentation, patient-reported outcomes, and longitudinal electronic health records into unified computational embeddings representing evolving patient biology. Self-supervised learning enables discovery of latent biological relationships without extensive manual annotation, while multimodal transformer architectures align heterogeneous biomedical modalities within shared representation spaces. Graph neural networks model biological interactions among molecular pathways, imaging phenotypes, tissue architecture, immune responses, therapeutic targets, and clinical outcomes.

These computational principles enable adaptive foundation models to function as continuously evolving biomedical intelligence systems supporting personalized oncology.[9]

4. Computational Architecture

Modern adaptive foundation model platforms consist of interconnected computational layers responsible for multimodal biomedical data acquisition, preprocessing, representation learning, continual adaptation, predictive analytics, digital twin simulation, and intelligent clinical decision support.[10]

The acquisition layer continuously integrates radiological imaging, digital pathology, genomic sequencing, transcriptomics, proteomics, metabolomics, epigenomics, spatial biology, laboratory investigations, circulating tumor DNA,

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wearable physiological monitoring, medication history, patient-reported outcomes, and electronic health records. Advanced preprocessing pipelines normalize imaging studies, harmonize molecular datasets, encode clinical narratives using natural language processing, and synchronize temporal patient information.

Foundation AI models subsequently generate generalized multimodal embeddings representing molecular biology, tissue architecture, imaging phenotypes, physiological function, and longitudinal clinical trajectories. Continual learning modules incorporate newly acquired biomedical evidence while preserving previously learned knowledge, thereby supporting adaptive precision oncology throughout clinical practice.[11]

5. Foundation Models as Adaptive Biomedical Intelligence

Foundation AI models provide the computational intelligence underlying adaptive oncology because they acquire generalized biomedical knowledge from massive multimodal datasets before specialization for individual clinical applications. Unlike conventional task-specific algorithms, foundation models develop transferable computational representations applicable across diagnosis, prognosis, biomarker discovery, therapeutic prediction, disease monitoring, computational pathology, radiomics, immunotherapy, and intelligent clinical decision support.[12]

Transformer architectures enable multimodal attention across imaging, pathology, molecular biology, laboratory investigations, wearable monitoring, and clinical documentation, while graph neural networks characterize interactions among genes, proteins, signaling pathways, immune responses, imaging phenotypes, therapeutic targets, physiological variables, and longitudinal clinical outcomes.

These generalized computational capabilities establish adaptive foundation models as continuously evolving biomedical reasoning systems supporting personalized cancer management.[13]

6. Multimodal Learning Across the Cancer Care Continuum

Adaptive foundation models depend upon comprehensive integration of heterogeneous biomedical modalities into unified patient-specific computational representations. Radiological imaging provides anatomical and functional characterization of tumors, while digital pathology contributes microscopic tissue architecture, immune infiltration, stromal remodeling, angiogenesis, fibrosis, necrosis, and cellular morphology. Multi-omics technologies—including genomics, transcriptomics, proteomics, metabolomics, epigenomics, immunomics, microbiomics, and spatial biology—provide detailed molecular characterization of evolving tumor biology.[14]

Wearable biosensors continuously monitor physiological parameters including heart rate, physical activity, sleep quality, treatment-related symptoms, medication adherence, and quality-of-life indicators. Laboratory biomarkers, physician documentation, environmental exposures, and electronic health records contribute longitudinal clinical context extending beyond conventional hospital-based assessments.

Artificial intelligence harmonizes these diverse modalities using multimodal transformers, graph neural networks, biological knowledge graphs, and cross-modal attention mechanisms capable of generating adaptive computational embeddings representing continuously evolving patient biology.[15]

7. Continual Learning in Clinical Oncology

Continual learning represents the defining capability of adaptive foundation models because it enables artificial intelligence to incorporate new biomedical information without catastrophic forgetting of previously acquired knowledge. Serial imaging examinations, computational pathology, liquid biopsy, laboratory biomarkers, wearable physiological monitoring, medication history, patient-reported outcomes, and longitudinal clinical trajectories are continuously integrated into evolving computational frameworks.[16]

Adaptive learning algorithms recognize emerging disease patterns, changing therapeutic responses,

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newly discovered biomarkers, evolving molecular alterations, and updated clinical guidelines while maintaining stability across previous clinical experience. Reinforcement learning further optimizes therapeutic recommendations by incorporating outcomes from prior treatment decisions into future computational reasoning.

These continuously adaptive capabilities enable oncology systems to remain synchronized with evolving patient biology and expanding biomedical knowledge while supporting real-time precision medicine.[17]

8. Adaptive Biomarker Discovery

Adaptive foundation models substantially enhance biomarker discovery by continuously integrating radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, wearable physiological monitoring, and longitudinal clinical outcomes into comprehensive multimodal computational frameworks. Artificial intelligence identifies emerging biological signatures associated with therapeutic sensitivity, immune activation, treatment resistance, toxicity, recurrence, metastatic progression, and survival while continuously refining computational biomarker performance as new clinical evidence becomes available.[18]

These adaptive computational biomarkers improve individualized therapeutic stratification, accelerate translational oncology research, and strengthen evidence-based precision medicine by evolving alongside advances in biomedical science and clinical practice.[19]

9. Adaptive Therapeutic Decision-Making

One of the most transformative applications of adaptive foundation models is personalized therapeutic decision-making through continuous integration of imaging phenotypes, histopathological characteristics, molecular biology, laboratory biomarkers, wearable physiological monitoring, medication history, and longitudinal clinical trajectories. Foundation AI models continuously refine predictions regarding responsiveness to chemotherapy, targeted therapy, endocrine therapy, immunotherapy, radiation therapy, surgery, and multimodal treatment combinations while adapting therapeutic recommendations according to evolving patient biology and real-world clinical outcomes.[20]

10. Digital Twins and Adaptive Virtual Patients

Digital twin technology represents one of the most advanced applications of adaptive foundation models by creating continuously evolving virtual representations of individual cancer patients synchronized with their biological counterparts. Foundation AI models integrate serial radiological imaging, digital pathology, genomics, transcriptomics, proteomics, metabolomics, laboratory biomarkers, circulating tumor DNA, wearable physiological monitoring, medication history, patient-reported outcomes, and longitudinal clinical information into adaptive computational patient models capable of simulating disease progression, therapeutic response, toxicity, recurrence, metastatic dissemination, and survival.[21]

Unlike conventional virtual patient models, adaptive digital twins continuously update their internal computational representations as new biomedical information becomes available. This enables simulation of changing tumor biology, emerging mechanisms of therapeutic resistance, immune adaptation, and evolving physiological status throughout diagnosis, treatment, follow-up, and survivorship.

These intelligent virtual ecosystems provide clinicians with opportunities to compare multiple therapeutic strategies before clinical implementation while supporting proactive precision oncology based on continuously evolving patient-specific biology.

11. Intelligent Clinical Decision Support

Adaptive foundation models provide the computational foundation for next-generation clinical decision-support systems capable of continuously integrating heterogeneous biomedical information into comprehensive patient-centered recommendations. Radiological imaging, digital pathology, molecular diagnostics, laboratory investigations, wearable physiological monitoring, medication history, physician documentation, patient-reported outcomes, and

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evidence-based clinical guidelines are synthesized into unified computational environments supporting multidisciplinary oncology practice.[22]

Interactive clinical dashboards generate individualized diagnostic summaries, adaptive biomarker analyses, digital twin simulations, therapeutic recommendations, toxicity estimates, recurrence probabilities, disease progression forecasts, and survival predictions while facilitating collaboration among oncologists, radiologists, pathologists, surgeons, radiation oncologists, molecular biologists, pharmacists, nurses, genetic counselors, and computational scientists.

These intelligent systems improve workflow efficiency, strengthen multidisciplinary communication, reduce information fragmentation, and promote evidence-based personalized cancer management across the entire oncology care continuum.

12. Precision Immuno-Oncology Through Adaptive Learning

Immunotherapy exemplifies the need for continuously adaptive computational intelligence because treatment response depends upon dynamic interactions among malignant cells, immune populations, stromal fibroblasts, endothelial cells, extracellular matrix components, cytokines, chemokines, and molecular signaling pathways. Adaptive foundation models continuously integrate computational pathology, radiomics, immunomics, spatial transcriptomics, genomics, proteomics, metabolomics, laboratory biomarkers, and longitudinal clinical outcomes into evolving computational representations of the tumor immune ecosystem.[23]

Graph neural networks characterize communication among immune cells and malignant populations while continually updating biological representations as therapeutic responses evolve. Reinforcement learning further optimizes immunotherapeutic recommendations through iterative evaluation of treatment outcomes, thereby supporting adaptive selection of immune checkpoint inhibitors, adoptive cellular therapies, cancer vaccines, bispecific antibodies, and combination immunotherapeutic strategies.

These continuously learning computational ecosystems substantially improve personalized precision immuno-oncology while adapting to changing immune biology throughout treatment.

13. Federated Continuous Learning Networks

Adaptive foundation models become increasingly powerful when developed through collaborative federated learning across geographically distributed healthcare institutions. Individual hospitals, cancer centers, and research organizations independently train local foundation models using radiological imaging, digital pathology, molecular diagnostics, laboratory investigations, wearable monitoring, and longitudinal clinical records while securely exchanging encrypted model parameters rather than identifiable patient information.[24]

This decentralized learning strategy enables adaptive models to continuously acquire new biomedical knowledge from diverse healthcare environments without compromising patient privacy or institutional governance. As participating institutions contribute increasingly diverse clinical experiences, foundation AI models become progressively more robust, fair, and generalizable across populations, healthcare systems, imaging platforms, and molecular technologies.

Federated continual learning therefore establishes globally distributed computational oncology ecosystems capable of continuously improving predictive performance while maintaining responsible data stewardship.

14. Explainability, Validation, and Responsible Clinical Implementation

Successful implementation of adaptive foundation models requires transparent, interpretable, reproducible, and rigorously validated artificial intelligence systems capable of maintaining clinician confidence and patient trust while continuously evolving. Explainable artificial intelligence (XAI) enables healthcare professionals to understand computational reasoning through attention visualization, saliency maps, SHAP (Shapley Additive Explanations), feature attribution analysis, uncertainty estimation, and counterfactual explanations

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identifying the imaging, molecular, pathological, physiological, and clinical variables responsible for adaptive predictions.[25]

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

Responsible implementation further depends upon protection of patient privacy, informed consent, transparency, accountability, equitable access, responsible governance, and continuous post-deployment surveillance to ensure safe integration of adaptive foundation models into routine oncology practice.

15. Future Perspectives

Future adaptive foundation model ecosystems will increasingly integrate multimodal large language models, agentic artificial intelligence, graph neural networks, reinforcement learning, federated continual learning, digital twins, spatial multi-omics, liquid biopsy, quantum computing, Internet of Medical Things (IoMT) technologies, robotics, cloud-native healthcare infrastructure, and autonomous clinical reasoning systems into unified intelligent oncology platforms.[26]

These next-generation computational ecosystems will continuously integrate molecular biology, imaging, pathology, laboratory medicine, wearable physiological monitoring, environmental exposures, electronic health records, biomedical literature, 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 adaptive ecosystems are expected to transform oncology from static clinical decision-making toward predictive, preventive, continuously learning, and dynamically personalized precision healthcare.

16. Discussion

Adaptive foundation models represent one of the most important paradigm shifts in computational oncology by replacing static artificial intelligence with continuously evolving biomedical intelligence capable of learning throughout the cancer care continuum. Unlike conventional machine learning systems that remain fixed after deployment, adaptive foundation models continuously integrate multimodal biomedical information while preserving previously acquired knowledge, thereby supporting diagnosis, biomarker discovery, prognostic prediction, therapeutic optimization, digital twins, intelligent clinical decision support, and personalized cancer management.[27]

Applications spanning computational pathology, radiogenomics, precision immunotherapy, adaptive therapeutics, continuous biomarker discovery, digital twins, federated learning, survivorship management, and longitudinal disease monitoring demonstrate the extraordinary translational potential of adaptive computational oncology. Nevertheless, successful implementation requires continued advances in multimodal data harmonization, explainable artificial intelligence, interoperability, computational infrastructure, cybersecurity, regulatory science, ethical governance, and sustained multidisciplinary collaboration.

As biomedical knowledge expands and healthcare systems become increasingly data-driven, adaptive foundation models are expected to become the computational backbone of future precision oncology.

17. Conclusion

Adaptive foundation models are redefining personalized cancer management by integrating radiological imaging, digital pathology, multi-omics, laboratory biomarkers, wearable technologies, electronic health records, digital twins, and longitudinal clinical intelligence into continuously evolving computational ecosystems capable of supporting predictive, preventive, adaptive, and personalized oncology throughout the disease continuum.[28]

Advances in transformer architectures, multimodal learning, graph neural networks, self-

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supervised learning, continual learning, federated learning, reinforcement learning, digital twins, multimodal large language models, agentic AI, and generative artificial intelligence are expected to further strengthen these intelligent ecosystems, enabling increasingly accurate diagnosis, adaptive biomarker discovery, molecular characterization, therapeutic optimization, disease surveillance, predictive clinical decision-making, and continuously personalized oncology care.[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, industry partners, and regulatory agencies will accelerate the responsible implementation of adaptive foundation models. These innovations have the potential to improve patient outcomes, enhance healthcare efficiency, reduce disparities in cancer care, accelerate translational research, and establish a new era of intelligent, continuously learning, and precision-guided oncology worldwide.[30]

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