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Review Article

Generative Artificial Intelligence for Clinical Decision Support in Oncology

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Cancer remains a leading cause of global morbidity and mortality, necessitating innovative approaches to clinical decision-making. Generative artificial intelligence (GenAI) powered by the increasingly large amount of accumulating clinical, molecular, and radiomics data about cancer patients and their treatments may serve as the kernel of rapid learning decision-support systems that could enable personalized cancer treatments to counter therapeutic resistance and overcome the shortcomings of the current standard of care. [1] This narrative review examines recent advancements in generative AI, particularly large language models (LLMs) and multimodal AI systems, for clinical decision support in oncology. We present the fundamental architectures underlying these technologies, including transformer-based models and clinical natural language processing systems. The applications across the cancer care continuum are explored, encompassing diagnosis support, treatment planning, radiology and pathology assistance, precision oncology, and clinical trial matching. While LLMs offer a promising avenue for supporting clinical decision-making, enhancing patient care, and accelerating research, they face limitations that must be addressed before clinical adoption, including risks of hallucinations, poor generalisation, ethical concerns, and scope integration. [2] Current evidence demonstrates significant potential for improving diagnostic accuracy, workflow efficiency, and personalized medicine delivery, yet challenges related to hallucinations, data bias, regulatory frameworks, and explainability require careful consideration. Future directions emphasize multimodal AI integration, human-AI collaboration, and the development of robust regulatory frameworks to ensure safe and effective clinical implementation.

Keywords: Generative artificial intelligence, large language models, clinical decision support, oncology, precision medicine, deep learning, transformer architecture.

INTRODUCTION

Cancer represents one of the most formidable challenges facing modern healthcare systems worldwide. Cancer is a major medical problem worldwide. Due to its high heterogeneity, the use of the same drugs or surgical methods in patients with the same tumor may have different curative effects, leading to the need for more accurate treatment methods for tumors and personalized treatments for patients. [3] The complexity of oncological care, characterized by tumor heterogeneity, rapidly evolving therapeutic landscapes, and the necessity for individualized treatment approaches, has created an urgent need for sophisticated decision support systems capable of synthesizing vast amounts of clinical, molecular, and imaging data. Artificial intelligence (AI) promises to be the next revolutionary step in modern society, with AI-based decision-making tools in clinical oncology leading to more comprehensive, personalized therapy approaches. In clinical oncology, almost all patients receive a treatment recommendation in a multidisciplinary cancer conference at the beginning and during their

treatment periods. These highly complex decisions are based on a large amount of information of the patients and of the various treatment options, which need to be analyzed and correctly classified in a short time. [4] Traditional clinical workflows often struggle to integrate the exponentially growing body of medical knowledge with individual patient characteristics, potentially leading to suboptimal treatment decisions and missed therapeutic opportunities. The emergence of generative artificial intelligence, particularly large language models, has catalyzed a paradigm shift in healthcare applications. Large language models (LLMs) are artificial intelligence (AI) tools specifically trained to process and generate text. LLMs attracted substantial public attention after OpenAI's ChatGPT was made publicly available in November 2022. LLMs can often answer questions, summarize, paraphrase and translate text on a level that is nearly indistinguishable from human capabilities. [5] These advanced computational systems possess unprecedented capabilities in understanding, generating, and reasoning about complex medical information, positioning them as potentially transformative tools for clinical decision support. This article explores the role of artificial intelligence in medical oncology, emphasizing its impact on treatment decision-making for adult and pediatric cancer care. AI applications, including advanced imaging, drug discovery, and clinical decision support systems, enhance precision, personalization, and efficiency. [6] The integration of AI into oncology workflows promises to augment clinician capabilities, reduce diagnostic errors, and facilitate the delivery of precision medicine at scale. However, realizing this potential requires careful consideration of technical limitations, ethical implications, and regulatory requirements. Research into the potential benefits of artificial intelligence for comprehending the intricate biology of cancer has grown as a result of the widespread use of deep learning and machine learning in the healthcare sector and the availability of highly specialized cancer datasets. [7] This review examines the current state of generative AI for clinical decision support in oncology, synthesizing evidence from recent studies to provide a comprehensive overview of applications, benefits, challenges, and future directions. By critically evaluating the evolving landscape of AI-driven oncology tools, we aim to inform clinicians, researchers, and policymakers about both the transformative potential and the inherent limitations of these emerging technologies.

2. Fundamentals of Generative AI

2.1 Large Language Models and Transformer Architecture

Large Language Models (LLMs) recently demonstrated extraordinary capability, including natural language processing (NLP), language translation, text generation, question answering, and other tasks. LLMs are a new and essential part of computerized language processing, having the ability to understand complex verbal patterns and generate coherent and appropriate replies for the situation. [8] The foundation of modern generative AI lies in the transformer architecture, which has fundamentally altered approaches to natural language processing and medical AI applications. Transformers have dominated the field of natural language processing and have recently made an impact in the area of computer vision. In the field of medical image analysis, transformers have also been successfully used in full-stack clinical applications, including image synthesis/reconstruction, registration, segmentation, detection, and diagnosis. [9] The transformer architecture employs self-attention mechanisms that enable models to capture long-range dependencies within data, a capability particularly valuable for processing the complex, context-dependent information inherent in medical documentation. The proposal of the Transformer architecture marks a major breakthrough in natural language processing technology. It greatly improves the ability to handle long-distance dependencies through the attention mechanism, and has become the basic model for many NLP tasks. Large-scale pre-trained models such as GPT and BERT have shown significant improvements in performance by learning the subtle laws of language on large amounts of text data. [10] These architectural innovations have enabled the development of increasingly sophisticated medical AI systems capable of processing and generating clinical text with remarkable accuracy.

2.2 Clinical Natural Language Processing

Transformer architectures and large biomedical corpora pre-trained models have led to significant improvements in clinical NLP benchmarks, like BioBERT, ClinicalBERT and PubMedBERT. Meta-analysis results clearly show that models based on the RNN architecture (between 64.8% and 65.8% F1 in 2018–2019) are outperformed by those based on the BERT architecture (between 76.1% and 78.3% F1 in 2020–2022) and, in turn, by hybrid transformer models (from 87.8% to 89.7% F1 in 2023–2025). [11] The development of domain-specific language models has substantially advanced clinical NLP capabilities, enabling more accurate extraction and interpretation of medical information. There are few clinical language models, the largest of which trained in the clinical domain is comparatively small at 110 million parameters compared with billions of parameters in the general domain. GatorTron models scale up the clinical language model from 110 million to 8.9 billion parameters and improve five clinical NLP tasks including clinical concept extraction, medical relation extraction, semantic textual similarity, natural language inference, and medical question answering with 9.6% and 9.5% improvement in accuracy for NLI and MQA. [12] Scaling clinical language models has demonstrated substantial improvements across diverse medical NLP tasks, suggesting significant potential for integration into clinical workflows.

2.3 Multimodal AI in Medicine

Transformer is a promising neural network learner, and has achieved great success in various machine learning tasks. Thanks to the recent prevalence of multimodal applications and Big Data, Transformer-based multimodal learning has become a hot topic in AI research. [13] The integration of multiple data modalities represents a critical advancement for oncology applications, where clinical decision-making requires synthesis of imaging, genomic, and clinical information. The exceptionally rapid development of highly flexible, reusable artificial intelligence (AI) models is likely to usher in newfound capabilities in medicine. Generalist medical AI (GMAI) models will be capable of carrying out a diverse set of tasks using very little or no task-specific labelled data. Built through self-supervision on large, diverse datasets, GMAI will flexibly interpret different combinations of medical modalities, including data from imaging, electronic health records, laboratory results, genomics, graphs or medical text. [14] Foundation models represent an emerging paradigm in medical AI, offering the potential for versatile, adaptable systems capable of addressing diverse clinical tasks across the oncology care continuum.

3. Applications in Oncology Clinical Decision Support

3.1 Diagnosis Support

Artificial intelligence-based clinical decision support systems (AI-CDSS) provide a viable solution through advanced methodologies for comprehensive data analysis. AI-CDSS facilitate early cancer detection, precise staging, and personalized treatment planning by processing multimodal patient information through machine learning, computer vision, and natural language processing. These systems effectively interpret clinical results, identify critical disease patterns including clinical stage, site, tumor dimensions, histopathologic grading, and molecular profiles, and construct comprehensive patient profiles. [15] The application of LLMs to diagnostic support has demonstrated significant potential across various cancer types. DeepSeek demonstrated superior performance in diagnostic accuracy (F1-score: 89.2% vs ChatGPT's 76.5%, $P < 0.001$) and treatment alignment with guidelines ($\kappa = 0.82$ vs 0.67, $P = 0.003$). ChatGPT exhibited strengths in patient communication, generating layman-friendly explanations (readability score: 8.2/10 vs DeepSeek's 6.5/10, $P = 0.012$). Both models showed limitations in rare cancer subtypes (e.g., cholangiocarcinoma), with accuracy dropping below 60%. [16] These findings underscore the complementary strengths of different AI systems and the importance of selecting appropriate tools for specific clinical tasks.

GPT-4-based ChatGPT demonstrates significant potential in various industries; however, its potential clinical applications remain largely unexplored. ChatGPT achieved an 87% accuracy without choices and a 97% accuracy with choices, after excluding image-based quizzes. ChatGPT excelled in the Diagnosis category, attaining 89% accuracy without choices and 98% with choices, demonstrating

potential for diagnostic applications, suggesting its usefulness in supporting healthcare professionals in making differential diagnoses. [17]

3.2 Treatment Planning

A cross-sectional observational study involving 1,977 patients at high risk for recurrent or metastatic breast cancer examined the impact of a clinical decision support system on breast cancer treatment decisions and adherence to National Comprehensive Cancer Center guidelines. Treatment decisions changed in 105 (5%) of 1,977 patients and were concentrated in those with hormone receptor-positive disease or stage IV disease in the first-line therapy setting (73% and 58%, respectively). Reasons cited for changes included consideration of the CDSS therapeutic options (63% of patients), patient factors highlighted by the tool (23%), and the decision logic of the tool (13%). Adherence to NCCN treatment guidelines increased slightly after using the CDSS (0.5%; P = .003). [18] An explainable AI system designed to reproduce multidisciplinary cancer conference-based treatment decisions for metastatic and non-metastatic prostate cancer analyzed 5478 MCC cases including 76 clinical input variables and 23 treatment output parameters. The AI system generated automated treatment recommendations with high predictive accuracy across both hierarchical levels. For high-level categories, F1-scores reached 0.89 for surgery and 0.81 for radiation therapy. For detailed recommendations, F1-scores reached 0.99 for prostatectomy and 0.98 for PSMA-ligand therapy. [19] These results demonstrate the feasibility of AI systems in replicating expert consensus decisions within multidisciplinary tumor boards.

3.3 Radiology and Pathology Assistance

Clinical workflows in oncology rely on predictive and prognostic molecular biomarkers. Advances in deep learning, an artificial intelligence technology, have enabled the extraction of previously hidden information directly from routine histology images of cancer, providing potentially clinically useful information. DL has been used for advanced image analysis tasks, which have the potential of directly affecting clinical decision-making processes, including inference of molecular features, prediction of survival and end-to-end prediction of therapy response. [20] A convolutional neural network was trained to predict clinically significant prostate cancer from T2-weighted images, diffusion-weighted images, apparent diffusion coefficient maps, and T1-weighted contrast-enhanced images. Among 5735 examinations in 5215 patients, 1514 examinations showed csPCa. In the internal test set (400 examinations), the AUC was 0.89 and 0.89 for the DL classifier and radiologists, respectively. In the external test set (204 examinations), the AUC was 0.86 and 0.84 for the DL classifier and radiologists, respectively. [21] Deep learning models have achieved radiologist-level performance in detecting clinically significant cancers, suggesting significant potential for augmenting clinical workflows. The development of digital pathology and progression of state-of-the-art algorithms for computer vision have led to increasing interest in the use of AI, especially deep learning-based AI, in tumor pathology. The DL-based algorithms have been developed to conduct all kinds of work involved in tumor pathology, including tumor diagnosis, subtyping, grading, staging, and prognostic prediction, as well as the identification of pathological features, biomarkers and genetic changes. [22]

3.4 Precision Oncology and Genomics

In oncology, by mining the underlying connection between a text or image input and the desired output, LLMs demonstrate great potential for managing tumours. LLMs play a role in cancer screening and diagnosis, metastasis identification, tumour staging, treatment recommendation, and documentation processing tasks by decoding various types of clinical data. [23] By integrating an expert-curated dataset with RAG, LLMs can accurately suggest evidence-based therapies across various cancer types, which may facilitate precision oncology investigations. Leveraging structured text and RAG improved model performance by 43% relative to a general-purpose LLM (94% vs. 65.8%), highlighting the benefit of integrating external knowledge for better therapeutic recommendations. [24] Retrieval-augmented generation approaches demonstrate substantial improvements in matching patients to appropriate targeted therapies based on genomic profiles. This study assessed various ChatGPT versions' ability to generate accurate next-generation sequencing reports

and treatment recommendations for NSCLC. Analyzing 160 responses, GPT-4 outperformed GPT-3.5, showing higher base score (90% v 60%; P < .01) and fewer hallucinations (34% v 53%; P < .01). GPT-4's overall G-PS was significantly higher (0.34 v –0.15; P < .01), indicating superior performance in matching treatment recommendations with biomarkers in precision oncology. [25]

3.5 Clinical Trial Matching

TrialMatchAI is an AI-powered recommendation system that automates patient-to-trial matching by processing heterogeneous clinical data, including structured records and unstructured physician notes. Built on fine-tuned, open-source large language models within a retrieval-augmented generation framework, TrialMatchAI ensures transparency and reproducibility. In real-world validation, 92% of oncology patients had at least one relevant trial retrieved within the top 20 recommendations, with expert assessment validating over 90% accuracy in criterion-level eligibility classification. [26]

A multi-agent AI platform underpinned by an oncology-specific knowledge graph screened 3,804 patients and identified 23,912 trials, with 17,912 confirmed after expert review. Time-to-recommendation was under one week from screening to final recommendations. Performance metrics demonstrated Sensitivity of 0.8375, Specificity of 0.8359, Precision of 0.8121, and F1 Score of 0.8246, significantly outperforming zero-shot or frontier GPT-based models. [27] Specialized AI platforms for clinical trial matching substantially outperform general-purpose LLMs, highlighting the importance of domain-specific optimization.

A demonstration project combining AI clinical decision support with expert consultation for NGS testing showed that over 30% of treatment decisions were altered based on CDS AI plus expert review. All NGS tests were ordered via platform automation with testing taking 16 days, and all patients had NGS results that impacted therapeutic options, including 42% with two or more therapy matches and 22% with options beyond the NGS report. [28]

4. Current Models and Systems

4.1 GPT-Based Systems

ChatGPT has been used to generate accurate differential diagnosis lists, support clinical decision-making, optimize clinical decision support, and provide insights for cancer screening decisions. In addition, ChatGPT has been used for intelligent question-answering to provide reliable information about diseases and medical queries. In terms of medical documentation, ChatGPT has proven effective in generating patient clinical letters, radiology reports, medical notes, and discharge summaries, improving efficiency and accuracy for health care providers. [29]

GPT-4's performance was examined on 643 Congress of Neurological Surgeons Self-Assessment Neurosurgery Exam board-style questions. GPT-4 attempted 91.9% of questions and achieved 76.6% accuracy, increasing to 79.0% for text-only questions. GPT-4 outperformed ChatGPT ($p<0.001$) and exceeded the performance of medical students (26.3%), neurosurgery residents (61.5%), and the national average of SANS users (69.3%) across all categories. [30]

A prospective study evaluated the compatibility of AI (ChatGPT-4.0) with multidisciplinary tumor council decisions in 100 cancer patients. A high concordance rate of 76.4% was observed between AI and MDT decisions ($\kappa = 0.764$, $p < 0.001$). Most inconsistencies arose in cases requiring individualized decisions, indicating AI's current limitations in incorporating contextual clinical judgment. [31]

4.2 Med-PaLM and Domain-Specific Models

Using a combination of prompting strategies, Flan-PaLM achieves state-of-the-art accuracy on every MultiMedQA multiple-choice dataset including 67.6% accuracy on MedQA (US Medical Licensing Exam-style questions), surpassing the prior state of the art by more than 17%. Med-PaLM, the resulting model from instruction prompt tuning, performs encouragingly but remains inferior to clinicians. Comprehension, knowledge recall and reasoning improve with model scale and instruction prompt tuning, suggesting the potential utility of LLMs in medicine. [32]

Med-PaLM 2 scores up to 86.5% on the MedQA dataset, improving upon Med-PaLM by over 19%, and demonstrates dramatic performance increases across MedMCQA, PubMedQA and MMLU clinical topics datasets. Detailed human evaluations show that physicians prefer Med-PaLM 2 answers to those from other physicians on eight of nine clinical axes. In a pilot study using real-world medical questions, specialists preferred Med-PaLM 2 answers to generalist physician answers 65% of the time. [33] Med-PaLM 2 represents a significant advancement in medical LLMs, demonstrating the value of domain-specific fine-tuning for clinical applications.

4.3 Hospital-Integrated AI Systems

An AI tool, Watson for Oncology, used for the treatment of cancer has been implemented in several different settings, including Brazil, China, India, South Korea, and Mexico. By focusing on the implementation of an AI-based clinical decision support system for oncology, this demonstrates how AI can be both beneficial and challenging for cancer management globally and particularly for low-middle-income countries. [34] Generative AI enhanced with agentic AI and vector-based RAG, using only open-source tools and LLMs, produced reliable breast cancer summaries and treatment evaluations. A workflow involving modular LLMs iterating over patient notes extracted cancer-related information, with subsequent AI agents comparing extractions with mCODE summaries and evaluating against NCCN guidelines. No hallucinations were observed in outputted data and no incorrect interpretations were found. [35] Open-source, modular AI systems demonstrate promise for eliminating hallucinations through grounding and retrieval-augmented approaches.

5. Benefits and Clinical Impact

5.1 Accuracy Improvement

Deep learning models achieve high diagnostic accuracy in medical imaging. In ophthalmology, AUCs ranged between 0.933 and 1 for diagnosing diabetic retinopathy, age-related macular degeneration and glaucoma on retinal fundus photographs and optical coherence tomography. In respiratory imaging, AUCs ranged between 0.864 and 0.937 for diagnosing lung nodules or lung cancer on chest X-ray or CT scan. For breast imaging, AUCs ranged between 0.868 and 0.909 for diagnosing breast cancer on mammogram, ultrasound, MRI and digital breast tomosynthesis. [36]

Advanced LLMs showed high diagnostic accuracy (>90%) in common clinical scenarios, with Claude 3.7 achieving perfect accuracy (100%) in certain conditions. In complex cases, Claude 3.7 achieved the highest accuracy (83.3%) at the final diagnostic stage, significantly outperforming smaller models. [37] Leading LLMs demonstrate remarkable diagnostic capabilities that approach or exceed clinician performance in specific contexts.

5.2 Workflow Efficiency

Large language models have emerged as transformative tools in medicine, with strong capabilities in language understanding, reasoning, and structured information extraction. Radiation oncology is particularly well suited for LLM integration due to its data-intensive workflows, reliance on structured guidelines, and documentation burden. Applications include domain-specific fine-tuning for decision support, automated nomenclature standardization, registry curation using autonomous LLM agents, and protocol-aware radiotherapy plan evaluation. [38] ChatGPT-3.5 demonstrated the ability to extract pathological classifications with an overall accuracy of 89%, outperforming the performance of two traditional NLP methods. The results underscore the potential role of LLMs in transforming unstructured healthcare data into structured formats, thereby supporting research and aiding clinical decision-making without requiring extensive task-specific human annotation and model training. [39]

5.3 Personalized Medicine

Cancer research encompasses data across various scales, modalities, and resolutions, from screening and diagnostic imaging to digitized histopathology slides to various types of molecular data and clinical records. The integration of these diverse data types for personalized cancer care and predictive modeling holds the promise of enhancing the accuracy and reliability of cancer screening, diagnosis, and treatment. [40] For 10 fictional cancer patients, a

median number of 4.0 treatment options was identified by the human expert compared with higher numbers from LLMs. For each patient, at least one LLM generated a treatment option considered helpful by MTB members. Two unique useful treatment options were identified only by LLM, highlighting that LLMs can complement established precision oncology procedures despite not yet reaching the quality of human experts. [41]

CHALLENGES AND LIMITATIONS

6.1 Hallucinations

A significant risk associated with the use of LLMs is their potential to create hallucinations. Hallucinations (false information) generated by LLMs arise from a multitude of causes, including both factors related to the training dataset as well as their auto-regressive nature. The implications for clinical practice range from the generation of inaccurate diagnostic and therapeutic information to the reinforcement of flawed diagnostic reasoning pathways, as well as a lack of reliability if not used properly. [42] A framework for assessing clinical safety and hallucination rates of LLMs for medical text summarization demonstrated that by refining prompts and workflows, major errors were successfully reduced below previously reported human note-taking rates. Clinical error metrics derived from 18 experimental configurations involving LLMs for clinical note generation, consisting of 12,999 clinician-annotated sentences, observed a 1.47% hallucination rate and a 3.45% omission rate. [43] Medical large language models are vulnerable to data-poisoning attacks. Replacement of just 0.001% of training tokens with medical misinformation results in harmful models more likely to propagate medical errors. Furthermore, corrupted models match the performance of their corruption-free counterparts on open-source benchmarks routinely used to evaluate medical LLMs, making detection challenging. [44]

6.2 Data Bias

Large language models are increasingly integrated into healthcare for clinical decision support and patient communication. Although these models can pass explicit social bias tests, they may retain implicit biases that could influence medical judgment. All 10 models examined exhibited systematic implicit biases across all categories, with the strongest biases observed in Race (Mean = 0.61) and Socioeconomic Status (Mean = 0.56). Stronger implicit associations significantly predicted discriminatory choices in downstream medical decision tasks ($p < 0.001$). [45] LLMs often proposed inferior treatments when patient race was explicitly or implicitly indicated, though diagnostic decisions demonstrated minimal bias. These findings underscore critical concerns about the potential for AI to perpetuate racial disparities in mental healthcare, emphasizing the necessity of rigorous bias assessment in algorithmic medical decision support systems. [46]

6.3 Regulatory and Ethical Issues

AI integration in oncology is transforming therapeutic decision-making by providing clinical decision support. AI may improve treatment precision, but it raises ethical, legal, and informed consent issues. Key concerns include algorithmic transparency, unclear accountability in AI-guided decisions, data privacy, and gaps in patient understanding of AI's role in their care. [47] The regulation of GPT-4 and generative AI in medicine and healthcare without damaging their exciting and transformative potential is a timely and critical challenge to ensure safety, maintain ethical standards, and protect patient privacy. Regulatory oversight should assure medical professionals and patients can use LLMs without causing harm or compromising their data or privacy. [48]

6.4 Explainability

While LLMs have achieved excellent performance on medical licensing exams, these tests fail to assess many skills necessary for deployment in a realistic clinical decision-making environment, including gathering information, adhering to guidelines, and integrating into clinical workflows. Current state-of-the-art LLMs do not accurately diagnose patients across all pathologies, follow neither diagnostic nor treatment guidelines, and cannot interpret laboratory results, posing a serious risk to the health of patients. [49] An explainable artificial intelligence model for clinically significant PCa diagnosis at biparametric MRI using PI-RADS features for classification justification achieved an area under the receiver operating characteristic curve of 0.89 in internal and

0.87 in external test sets. XAI-assisted readings improved the confidence of nonexperts in assessing PI-RADS 3 lesions, reducing reading time by 58 seconds while providing visual and textual explanations using well-established imaging features. [50]

FUTURE DIRECTIONS

7.1 Multimodal AI

Multimodal artificial intelligence methods are now a paradigm-shifting approach for cancer prognosis and diagnosis, allowing the blending of heterogeneous data modalities including histopathology images, radiomics, genomics, and clinical data. Comparative analysis demonstrated that transformer-based and hybrid models offered the highest mean AUC and concordance index measures (0.93 and 0.91, and 0.89 and 0.88, respectively). [51] Pathomic Fusion represents an interpretable strategy for end-to-end multimodal fusion of histology image and genomic features for survival outcome prediction. Results demonstrate that the proposed multimodal fusion paradigm improves prognostic determinations from ground truth grading and molecular subtyping, as well as unimodal deep networks trained on histology and genomic data alone. [52] Integrated approaches combining imaging and genomic data consistently outperform unimodal methods, pointing toward the importance of comprehensive multimodal systems in future oncology AI.

7.2 Human-AI Collaboration

Evidence from head and neck oncology remains early-stage and heterogeneous, dominated by simulation-based and small cohort studies with limited real-world validation. GenAI performs best in structured, language-based tasks such as clinical documentation, case summarization, and patient education. GenAI shows promise as an assistive tool but is not yet suitable for autonomous clinical decision-making. Prospective, workflow-integrated evaluation and standardized validation are needed before safe clinical adoption. [53] A study evaluating LLMs as alternative to rule-based alert systems focusing on their ability to identify prescribing errors demonstrated that the co-pilot arm (pharmacist plus LLM-based CDSS) achieved the best performance with an accuracy of 61%. In detecting errors posing serious harm, the co-pilot mode increased accuracy by 1.5-fold over the pharmacist alone, demonstrating that effective LLM integration for complex tasks can enhance healthcare professional performance. [54]

7.3 Regulatory Frameworks

The upcoming evolutionary leap involves the transition from an AI-powered model primarily designed for answering medical questions to a more versatile and practical tool for healthcare providers such as generalist biomedical AI systems for multimodal-based calibrated decision-making processes. The development of more accurate virtual clinical partners could enhance patient engagement, offering personalized support, and improving chronic disease management. [55] With generative AI continuing to make inroads in healthcare, assessing LLMs with human evaluations is essential to assuring safety and effectiveness. A comprehensive framework for human evaluation of LLMs covering three phases of workflow, Planning, Implementation and Adjudication, and Scoring and Review, is designed with five proposed evaluation principles: Quality of Information, Understanding and Reasoning, Expression Style and Persona, Safety and Harm, and Trust and Confidence. [56]

CONCLUSION

Generative artificial intelligence, particularly large language models and multimodal AI systems, represents a transformative technology for clinical decision support in oncology. Integration of GAI into oncology has shown some ability to enhance diagnostic accuracy, optimize treatment decisions, and improve clinical efficiency, ultimately strengthening the patient-physician relationship. Despite these advancements, the inherent stochasticity of GAI's performance necessitates human oversight, more specialized models, proper physician training, and robust guidelines to ensure its well tolerated and effective integration into oncologic practice. [57] The evidence reviewed demonstrates substantial progress across multiple applications, from diagnosis support and treatment planning to precision oncology and clinical trial matching. Current systems have achieved performance levels that approach or exceed human clinicians in specific,

well-defined tasks. However, significant challenges remain, including the risk of hallucinations, persistent biases in model outputs, regulatory uncertainties, and limitations in model explainability. Without human oversight, guidance and responsible design and operation, generative AI applications will remain a party trick with substantial potential for creating and spreading misinformation or harmful and inaccurate content at unprecedented scale. However, if positioned and developed responsibly as companions to humans augmenting but not replacing their role in decision making, knowledge retrieval and other cognitive processes, they could evolve into highly efficient, trustworthy, assistive tools for information management. [58] The future of AI in oncology lies in the development of multimodal systems capable of integrating diverse data sources, establishment of robust human-AI collaboration frameworks, and creation of comprehensive regulatory guidelines. The convergence of multimodal data, federated architectures, and biological knowledgebases has the potential to enable rapid clinical translation, bridging research and practice to redefine personalized cancer care and improve survival outcomes across diverse cancer subtypes. [59] As these technologies mature, their responsible integration into clinical workflows promises to enhance the precision, efficiency, and personalization of oncology care, ultimately improving outcomes for cancer patients worldwide.

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