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Knowledge Graph–based Approaches for Personalized Cancer Treatment in Medical Oncology: A Review and Conceptual Framework

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***Abstract*—Personalized management of cancer patients has become increasingly important in medical oncology, as significant genetic, molecular, and clinical heterogeneity exists among cancer patients. Conventional cancer treatments typically rely on standardized protocols, which often fail to account for individual patient variability, leading to heterogeneous therapeutic responses. In the last few years, knowledge graphs (KGs) have started to be used as a powerful platform for integration of diverse biomedical data sources and precision oncology applications. In this review, we examine how recent knowledge graph–based methods for personalized treatment of cancer focusing on their structural configuration, data analysis, and clinical relevance. Although prior works show that there has been progress in building disease-specific and multi-omics KGs, most proposed systems are still confined to static representations, fragmented data integration practices and lack of real-world clinical validation. Extra considerations regarding interoperability, interpretability of AI-based models and a clinician backed usability limit their translational potential. Upon critical review of existing literature, this study delineates the research gaps and proceeds to describe a consensual abstract model for an end-to-end operationalized knowledge graph pipeline talking about clinical, genomics, and research data. The proposed framework emphasizes interpretable learning and incremental knowledge updating to support clinically meaningful and personalized treatment recommendations.**

***Index Terms*— Knowledge Graphs, Personalized Cancer Treatment, Precision Oncology, Medical Decision Support Systems, Multi-Omics Data Integration.**

I. Introduction

Cancer is still one of the most difficult diseases for modern medicine and is a contributing cause for a considerable percentage of deaths all over the globe despite constant innovations in diagnostic and therapeutic technologies. There are enormous variations in cancer incidence rates, development, treatment response rates, and survival rates among largescale studies conducted among patients and of different types of cancer. In many cases we see great diversity at a genetic and molecular level in certain types of cancer which in turn shows us that cancer is a very heterogeneous disease; this is a great challenge for the traditional therapeutic approaches which we tend to design for all patients based on certain clinical criteria [1–4].

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To get over the issues of a one size fits all approach we have seen the rise of personalized cancer therapy which is what precision oncology is all about. Precision oncology puts forth the idea of tailoring treatment plans to each individual patient based on their unique features which may include genomic changes, molecular profiles and also how that patient has responded to treatments in the past. Advancements in high throughput sequencing technologies and multi-omics platforms have grown to greatly increase what is available in terms of patient specific data which in turn is enabling more in depth study of tumor biology and the disease [3–7]. Relevant data in cancer research is scattered across various sources with different formats and terminologies, which makes it difficult to interpret and integrate [8-11].

In recent years, knowledge graphs have been identified as an emerging computing paradigm which holds great promise in dealing with challenges posed by heterogeneous data integration in oncology. Since knowledge graphs allow biomedical entities like diseases, genes, drugs, biomarkers, and clinical features to be modeled as nodes in a network, which are connected based on semantically defined relationships, knowledge graphs provide efficient mechanisms not only for integrated data management, but also for querying, reasoning, and inferential tasks based on multiple sources [12, 13]. There have been studies which have explored the ability of knowledge graphs in dealing with tasks like cancer registry analyses, multi-omics data integration, drug repositioning, and clinical evidences, which indicate an increasing trend of knowledge graphs in precision oncology studies [14–16].

Despite the fact that there is great interest in knowledge graph based approaches we see that which which has not translated into their use in everyday clinical practice. At present we see that the majority of these systems are built around static graphs which were designed for a certain task at hand and are not updated to include the ever growing body of clinical research or which report changing patient outcomes. The practical adoption is further limited by the challenges with the systems inter-operability and integration with longitudinal patient data, absence of adequate real world validation, and limitations in longitudinal patient data integration. Collectively, these challenges indicate the need for the refinement of these systems in a manner that can provide clinically relevant, flexible, and comprehensible knowledge frameworks that more closely integrate with clinical workflows and demands of tailored oncology [15–18, 20–25].

II. Objectives of the Study

This review's main goal is to study in great detail the role of knowledge graph based approaches in the field of personal cancer treatment which is a part of medical oncology. Despite the increasing attention that knowledge graphs have drawn recently in biomedical research, their practical value in enabling clinically useful and interpretable precision oncology solutions remains uneven and insufficiently examined.

The goal of the proposed work is to comprehensively survey and distill the current knowledge graph solutions related to the integration of heterogeneous oncology data. Based on the prior knowledge analyzed in the proposed project, the objectives will be to identify the impact of various design decisions on the integrated quality, analytical strength, explainability, and relevance to the medical domain. The proposed study will also examine the application of artificial intelligence and learning algorithms with graphs when implemented together with knowledge graphs in predictive modeling and decision-making processes in personalizing cancer treatment. We put forward the role of open reasoning systems which have the ability to improve trust and decision making in health care.

III. Literature Review

The initial stage applications involving knowledge representation in cancer research largely targeted the use of knowledge graphs to represent cancer registrars and biomedical documents in attempts to facilitate biomedical data accessibility while improving the use of medical semantics in querying. From the perspectives of clinical research, the initial applications were somewhat useful for data representation but lacked any particular applications on the biomedical front for influencing the specific treatment of individual cases. Early studies have shown that representations based on knowledge graphs are capable of effectively connecting structured clinical records with external biomedical resources, thus allowing for better secondary use of oncology data. These studies have thus shown that there is indeed technical feasibility in the application of graph semantics with large cancer data, thus lending support for integrative analysis. These early implementations were mostly designed with structural organization and exploration in mind, with less concern for personalization and real-time clinical utility. Thus, while the early work laid an important role in the application of knowledge graphs in oncology, their utility in personalization in treatment planning played an indirect role. [1, 2, 3]. On our analysis, the major

drawback of the early approaches is indeed not in terms of technical feasibility but in the lack of reasoning and clinical output.
After the first application of knowledge graphs to manage oncology knowledge, the next phase saw the expansion of applications to cover the integration of genomic/molecular knowledge with clinical evidence. To manage the semantic heterogeneity underlying biomedical data, the next phase applications were seen to incorporate knowledge graph frameworks based on ontologies. Nevertheless, according to literature findings, there are specific scalability and generalizability issues for disease-specific knowledge graphs.
One big move in cancer knowledge graphs now includes mixing different types of molecular data. This blend helps grasp the complex biology behind tumors. Yet, in spite of the methodological advantages, the reviewed bodies of literature illustrate the presence of some significant challenges in the use of multi-omics knowledge graphs in a more clinically applicable manner. At present, a new trend emerging is the combination of AI and ML, as well as the implementation of knowledge graphs, which improves the analysis abilities for cancer research. Graph-based learning algorithm.

IV. PROPOSED PLAN

Based on the critical gaps identified from the reviewed literature, this study proposes a conceptual and clinically oriented knowledge graph framework to support personalized cancer treatment in medical oncology. The proposed plan does not introduce a new algorithm or predictive model but rather focuses on tackling some persistent structural and translational limitations consistently observed in existing knowledge graph-based oncology systems related to fragmented data integration, static graph representations, limited explainability, and weak alignment with real-world clinical workflows.
One of the key aims of the proposed plan is allowing for the dynamic evolution of the knowledge graph. Relative to the assorted state-of-the-art approaches, none of which utilize dynamic graphs but rather uses the static graphs that are periodically updated with the new observations, treatment outcomes, and research results of the patients, it is suggested in this paper that there be frequent updates. Although the reasoning and the discovery of patterns can be supported with the assistance of the artificial intelligence and graph-based learning methods, the approach views interpretability as a design principle and a mandatory feature. The framework is concerned with clear reasoning paths and clinically meaningful explanations.
This proposed plan is highlighted by a distinct clinician-centered philosophy in design. Since it is clear that technical sophistication alone is not the key to clinical adoption, the framework has conceptually been formulated to align real-world oncology processes with best practices as to usability and compatibility with currently existing healthcare information systems. Clinicians are regarded as end-users. Fig 1 gives a high-level conceptual insight into the challenges noticed in the existing knowledge graph-based systems being deployed in the field of oncology and the knowledge graph design goals of the proposed system.

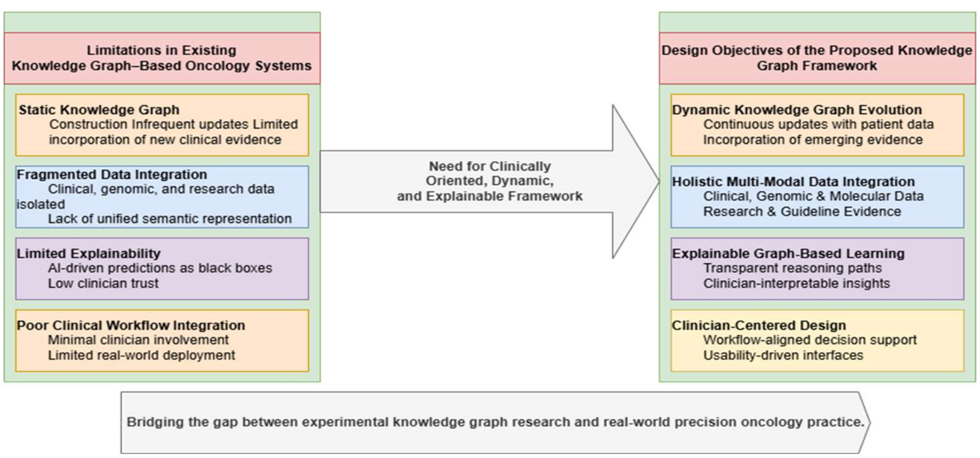

Figure 1. Conceptual illustration highlighting key limitations of existing knowledge graph–based oncology systems and the corresponding design objectives of the proposed clinically oriented, dynamic, and explainable Knowledge graph framework.

The above figure exemplifies how this proposed plan addresses the gap existing between knowledge graph research and practical applications involving precision oncology, using dynamic knowledge evolution, holistic integration, explainability, and alignment.

V. METHODOLOGY

Insofar as this paper is a type of literature review and conceptual framework proposition, its methodological scope lays firmly in analysis synthesis and conceptual modeling. The role of this section is to enunciate a process workflow tailored to a system based on knowledge graph construction for personalized cancer therapy.

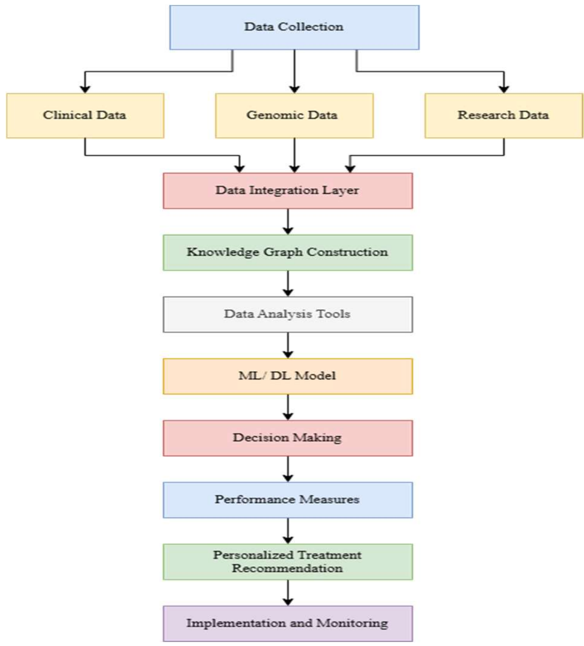

Figure 2. Overview of the proposed knowledge graph–based methodological workflow for personalized cancer treatment.

Fig. 2 integrated heterogeneous oncology data, semantic harmonization using an oncology-specific ontology, dynamic construction of knowledge graphs, explainable analytics, clinical decision support, and feedback-driven knowledge evolution.

Source: Authors' own conceptualization based on literature review.

The methodological pipeline starts with the identification and integration of diverse cancer data sources. Patient data are the central focus of the model and encompass the capture of the patient's demographics, information on cancer diagnosis, the staging of cancer disease progression, experiences related to cancer treatments, and the resulting outcomes typically captured within the electronic records of the cancer patients. Genomics/molecular information is also theoretically integrated to provide information related to cancer mutations specific to the disease. There is the integration of research cancer evidence typically sourced from biomedical literature.

In view of the disparate formats, terms, and sources, there is heavy emphasis on semantic harmonization as a precursor to knowledge graph construction. Indeed, conceptual data preparation is utilized to cope with discrepancies, missing data, and terminological differences. A domain ontology adapted to suit medical oncology is used as an intermediary tool to standardize ways of describing essential components like diseases, genes, medications, biomarkers, pathways, and treatment responses, as well as their significant associations.

After the semantic alignment, the combined data are conceptualized in the oncology knowledge graph. The biomedical/clinical entities are conceptualized as nodes, while the biological interactions/clinical associations are conceptualized as edges. The architecture of the oncology knowledge graph is tailored to capture molecular-level relationships such as gene pathway interactions and drug-target interactions, in addition to clinical-level relationships such as patient-treatment relationships and treatment outcomes. Personalized cancer treatment is based on the interrelationship between biological processes and clinical situations.

The suggested methodology implements conceptual graph analysis procedures in reasoning and insight following the construction of knowledge graphs. In contrast to other prediction-driven methods, the suggested workflow is also more focused on interpretability, which enables meaningful relationships and evidences to be analyzed in a manner that will be comprehensible to clinicians.

Lastly, there is a feedback refinement process within the methodology itself, which helps develop this knowledge continuously. As new clinical experience, treatment outcomes, or new research evidence emerges, there will be an opportunity to integrate this information conceptually into the knowledge graph. This helps to ensure the knowledge graph remains up to date with the latest trends and challenges encountered in cancer treatment.

VI. Results and Discussion

Rather than presenting performance results, this particular section would analyze particular methodological trends in the knowledge graph-based approaches for personalized treatments of cancer cases.

A. Insights from Existing Knowledge Graph–Based Approaches

From the literature, it can be realized that there have been numerous efforts put in by knowledge graph-based approaches in dealing with the unstructured cancer data from various sources. Registry-based knowledge graph approaches combined with ontologies have proved to be successful in providing structured clinical data for facilitating semantic searches in cancer.

However, the same review highlights that the functional domains of such systems are not extensive. The majority of the systems that employ the registry approach and ontology definition are focused on data representation and retrieval and lack the ability to reason about treatment on an individualized basis.

Table 1. Comparative Theoretical Analysis of Knowledge Graph–based Approaches for Personalized Cancer Treatment

Approach Category	Theoretical Focus	Key Contributions	Observed Limitations
Cancer registry–based knowledge graphs	Semantic organization of structured clinical data	Improved data accessibility and querying	Limited personalization, static representations
Ontology-driven precision oncology KGs	Standardization of cancer entities and relationships	Enhanced interoperability and semantic consistency	High dependency on predefined ontologies
Multi-omics knowledge graphs	Integration of genomic and molecular data	Identification of biomarkers and pathways	Weak linkage to real-world clinical outcomes
AI/GNN-enhanced knowledge graphs	Predictive modeling and pattern discovery	Improved survival and treatment response prediction	Limited explainability and clinical trust
Knowledge graph–based CDSS	Clinical decision support	Feasibility of KG-driven recommendations	Poor integration into routine workflows

In Table 1 above, it is shown that although semantic standardization and interoperability are improved by ontology-driven precision oncology knowledge graphs, they are commonly dependent on curated ontologies and datasets. This makes them inflexible, especially in the oncology field where constantly evolving new biomarkers and therapies emerge with regularly updated guidelines. The above-mentioned methods prove to be effective in understanding population-level information rather than dynamic and patient-specific treatment strategies. The existing ontology-driven knowledge graph and cancer registries are commonly data organization structures and do not provide any support to dynamic patient-specific strategies.

B. Role and Limitations of Multi-Omics Knowledge Graphs

Multi-omics knowledge graphs constitute a major methodological innovation by addressing molecular heterogeneity in the explicit manner of integrating data from the genomic, transcriptomic, proteomic, and epigenomic levels. It has been shown in numerous studies that such models aid in the discovery of biomarkers, pathway analysis, and the analysis of molecular mechanisms for cancer progress by capturing the relationships in genes, proteins, and pathways using multi-omics knowledge graphs.

Despite these strengths, the literature consistently suggests that most multi-omics knowledge graph implementations remain weakly connected to longitudinal clinical context. Integration of molecular data with patient-level information-such as treatment history, disease stage, and observed outcomes-is often incomplete. Validation is frequently limited to retrospective datasets or biological plausibility analyses, reducing immediate clinical applicability for these systems.

C. Role and Limitations of AI-Enhanced Knowledge Graph Analytics

Oncology knowledge graphs can also be analyzed more efficiently with the use of artificial intelligence methods, in particular, Graph Neural Networks and models based on embedding. The models with AI are more effective in predictive analytics, like the result of a treatment, survival analysis, analysis of progress in diseases, using the relationship dependencies that exist in the graphs. Graph-based learning performs better than the machine-learning models in comprehending the relationship dependencies among the entities in cancer.

Meanwhile, one of the weaknesses that one can identify when examining the reviewed studies is a general lack of explicability related to AI-assisted knowledge graph analytics. Most of the best performing models remain black boxes hence do not provide much understanding into clinical reasoning. In clinical oncology, where treatment decisions are often burdened with significant consequences, this also creates distrust among clinicians, besides raising ethical and regulatory concerns.

D. Clinical Decision Support and Translational Challenges

Based on knowledge graphs for clinical decision support systems (CDSS), knowledge graph-based CDSSs are the most straightforward approach for bridging computing achievements and practical applications for cancer treatment. Current research has shown the applicability of knowledge from the biomedical domain for assisting a clinician with diagnosis, prognostics, and therapeutic decisions. However, most existing systems have only been tested under retrospect or pilot conditions.

There exist some translational challenges discussed in the reviewed literature, such as lack of integration of the systems with hospital information technology, lack of clinician involvement in designing the systems, and usability.

TABLE II. COMPARISON OF REPRESENTATIVE KNOWLEDGE GRAPH FRAMEWORKS AND PROPOSED CONCEPTUAL FRAMEWORK

Aspect	Ontology-Driven Oncology KGs	AI-Enhanced Knowledge Graph Models	Knowledge Graph–Based CDSS	Proposed Conceptual Framework (This Study)
Primary Objective	Semantic standardization and data interoperability	Predictive modeling using graph-based learning	Clinical decision support for diagnosis or treatment	End-to-end personalized treatment support through dynamic and explainable knowledge integration
Data Integration Scope	Primarily structured clinical and curated biomedical data	Clinical and molecular data for prediction tasks	Selected clinical and guideline-based data	Holistic integration of clinical, genomic, molecular, and research evidence
Graph Update Strategy	Mostly static or periodically curated	Static training graphs with limited updates	Rule-based or manually updated	Continuous and feedback-driven graph evolution
Analytical Capability	Querying and semantic reasoning	High predictive accuracy using GNNs	Rule-based or inference-driven recommendations	Explainable graph-based learning combined with semantic reasoning
Explainability	High at semantic level, limited analytical depth	Limited (black-box predictive models)	Moderate (rule transparency)	Explicit emphasis on interpretable and clinician-understandable reasoning
Clinical Context Awareness	Limited patient-level personalization	Partial, often detached from longitudinal context	Focused on predefined workflows	Integrated longitudinal clinical context including treatment history and outcomes
Validation Setting	Experimental or registry-based studies	Retrospective datasets	Controlled or pilot deployments	Designed for real-world clinical alignment (conceptual, not experimental)
Scalability and Interoperability	Dependent on ontology coverage	Model-specific and data-dependent	Institution-specific implementations	Ontology-aligned, interoperable, and scalable framework design
Key Limitation	Limited personalization and adaptability	Lack of explainability and trust	Poor workflow integration	Addresses fragmentation, static design, and interpretability gaps collectively
Novel Contribution	Infrastructure-level support	Advanced analytics	Clinical feasibility	Unified, dynamic, explainable, and clinician-centered knowledge graph framework

To put these results into context, Table 2 is included below and illustrates similarities and differences between selected knowledge graph solutions and the conceptual framework proposed. It is easy to see from Table 2 that other solutions target disconnected aspects of personalized treatment for cancer patients, in contrast to this proposed framework. The future of personalized cancer treatment is expected to rely on conceptual frameworks that combine approaches dealing with dynamic knowledge evolution, explainability of analytics, and clinician-centered design.

E. Implications for Future Knowledge Graph Frameworks

In terms of the different categories of approaches assessed in the examined methods, there exist certain common drawbacks. In many of the knowledge graph approaches, there exist static or time-fluctuating structures of knowledge representation, which obviously hinders their adaptability to current medical data. In addition, though there have been remarkable enhancements in molecular data unification approaches, their coordination with the longitudinal medical context is still pending.

These arguments are pointing to the necessities and requirements of future and improved knowledge graph architectures that transcend the boundaries of incremental innovation. In their strategic models, the future architecture must emphasize more on the dynamic knowledge development, transparency in reasoning and a center-stage approach. It is also necessary to add the fact that innovation in this sphere will not be mainly through the introduction of more innovational blocks. The proposed conceptual framework that will be in this study is adequate to fulfill these imperatives.

VII. Conclusion

Precision medicine of cancer has become a major concern of contemporary cancer treatment, as it has acknowledged that cancer is a highly heterogeneous disease, genetically, molecularly, and clinically. The review has critically evaluated how knowledge graph approaches can be used to cope with this heterogeneity, which contributes to solving cancer-related data. The review has incorporated the results of a general evaluation of research and this highlights the use of knowledge graphs to establish complex association of cancer data between clinical, genetic, therapeutic and evidence bases.

Disease-specific and multi-omics graphs have ensured improved biological knowledge and predictive modeling of therapy response and outcome. In spite of these advances, it is determined in the context of this review that existing methods continue to be limited by factors such as a requirement to use a static graph, inadequate longitudinal clinical data, and the inability to explain AI-based predictions and a complete lack of validations in a clinical environment.

This points out the need to have a more balanced approach to experimental systems, knowledge graph and daily med-practice. The focus on making it possible to dynamically update a knowledge graph, a constant stream of knowledge, or even the reasoning based on an existing knowledge graph and so on are the factors that should be prioritized in the pursuit of a customized therapeutic strategy against cancer. The necessity to make a graph of knowledge explainable or the emphasis on a practitioner in the first place cannot be ignored.

References

[1] Hasan, S. M. S., Rivera, D., Wu, X.-C., Christian, J. B., & Tourassi, G. (2020). Knowledge graph–enabled cancer data analytics. IEEE Journal of Biomedical and Health Informatics, 24(7), 1831–1840. https://doi.org/10.1109/JBHI.2020.2990797

[2] Hasan, S. M. S., Rivera, D., Wu, X.-C., Christian, J. B., & Tourassi, G. (2019). A knowledge graph approach for the secondary use of cancer registry data. IEEE International Conference on Biomedical and Health Informatics (BHI), 1–4. https://doi.org/10.1109/BHI.2019.8834538

[3] Silva, M. C., Eugénio, P., Faria, D., & Pesquita, C. (2022). Ontologies and knowledge graphs in oncology research. Cancers, 14(8), 1906. https://doi.org/10.3390/cancers14081906

[4] Zhao, J., et al. (2019). Ontology-based knowledge graph for precision oncology. IEEE Transactions on Computational Biology and Bioinformatics.

[5] An, B. (2023). Construction and application of a breast cancer knowledge graph based on multi-source heterogeneous data. Mathematical Biosciences and Engineering, 20(3), 292–310. https://doi.org/10.3934/mbe.2023292

[6] Jin, S., Liang, H., Zhang, W., & Li, H. (2024). Knowledge graph for breast cancer prevention and treatment: A literature-based data analysis study. JMIR Medical Informatics, 12, e52210. https://doi.org/10.2196/52210

[7] Zhang, S., Zhao, J., Yuan, Q., & Wang, F. (2020). Biomedical knowledge graphs: Construction and applications. Journal of Biomedical Informatics, 107, 103422. https://doi.org/10.1016/j.jbi.2020.103422

[8] Chandak, P., et al. (2023). Precision medicine knowledge graph (PrimeKG): A multimodal view of diseases for precision medicine. Scientific Data, 10, 17. https://doi.org/10.1038/s41597-023-01960-3

[9] Huang, S., Chaudhary, K., & Garmire, L. X. (2017). More is better: Recent progress in multi-omics data integration methods. Frontiers in Genetics, 8, 84. https://doi.org/10.3389/fgene.2017.00084

[10] Li, Z., et al. (2018). Graph-based analysis of cancer pathways. IEEE/ACM Transactions on Computational Biology and Bioinformatics.

[11] Liu, Y., et al. (2020). Graph neural networks for cancer treatment prediction. IEEE Transactions on Medical Imaging.

[12] Wang, H., et al. (2021). Knowledge graphs for integrating electronic health records and genomic data. IEEE Journal of Biomedical and Health Informatics.

[13] Chen, X., et al. (2019). AI-driven knowledge graph for drug repurposing in cancer. Bioinformatics.

[14] Smith, A., et al. (2021). Radiogenomics knowledge graphs for personalized cancer care. IEEE Transactions on Radiation and Plasma Medical Sciences.

[15] Kim, S., et al. (2022). AI and knowledge graphs in oncology clinical trials. Cancers, 14(19), 4558.

[16] Yang, Q., et al. (2019). Knowledge graph–based approaches for targeted drug delivery in cancer. Journal of Controlled Release.

[17] Liu, J., et al. (2021). Integrative knowledge graph for cancer biomarker discovery. Briefings in Bioinformatics.

[18] Wang, X., et al. (2022). Knowledge graphs in immuno-oncology: Integrating immune-related data with cancer genomics. Frontiers in Immunology.
[19] Jackson, P., et al. (2021). Integrating social determinants of health into cancer knowledge graphs. Journal of Biomedical Informatics.
[20] Martin, E., et al. (2020). Knowledge graph–based personalization of radiotherapy. Physics in Medicine & Biology.
[21] Zhou, D., et al. (2023). AI-driven knowledge graph for precision oncology using multi-omics and clinical data. Nature Communications.
[22] Riedl, J., Moik, F., Esterl, T., Kostmann, S. M., Gerger, A., & Jost, P. J. (2023). Molecular diagnostics tailoring personalized cancer therapy—An oncologist's view. Virchows Archiv, 482(3), 459–467. https://doi.org/10.1007/s00428-023-03702-7
[23] He, J.-Y., et al. (2023). Patient-derived tumor models and their distinctive applications in personalized drug therapy. Molecular & Cellular Biomechanics, 20(2), 100014. https://doi.org/10.1016/j.mbm.2023.100014
[24] Lopes-Júnior, L. C., & Veronez, L. (2023). Personalized care for patients with cancer in the precision-medicine era. International Journal of Environmental Research and Public Health, 20(4), 3023. https://doi.org/10.3390/ijerph20043023
[25] Yang, J., et al. (2024). Condition-based knowledge graph for precision oncology (CPMKG). Database, baae102. https://doi.org/10.1093/database/baae102