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EXPLAINABLE AI-DRIVEN CLINICAL DECISION SUPPORT SYSTEMS IN PRECISION ONCOLOGY: INTERPRETABLE MODELS FOR MULTIMODAL CANCER CARE

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ABSTRACT

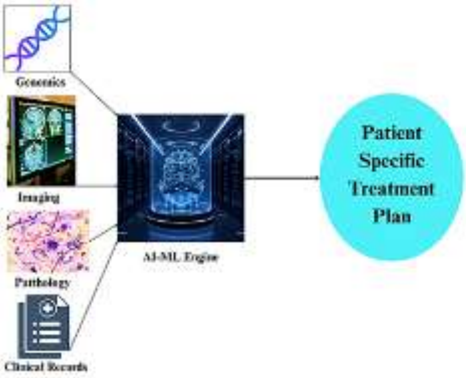
A potential advancement in precision oncology is AI in clinical decision support systems (CDSSs). In order to assist physicians in making more individualized treatment recommendations, AI can examine vast and complex data from electronic health records, radiology, histology, genetics, and other fields. Beyond biomarker-based patient classification, finding novel patterns and connections within and across various data sources is necessary. Risk is measured, diagnostic accuracy is improved, and patient outcomes, such as survival, treatment response, and recurrence, are predicted by AI applications in this field. Clinical Decision Support Systems (CDSS) with AI support may be able to synthesize data that cannot be interpreted by humans, allowing for the creation of brand-new biomarkers. The diagnosis of pulmonary nodules on a CT scan is consistent with AI models. Security of data, representation, and the ability to explain AI-based forecasts are still major obstacles. Up until 2025, over 139 peer-reviewed papers will cover a substantial patient database of solid and hemorrhagic cancers. AUC values of 0.82–0.96 for multimodal AI models versus 0.65–0.78 for single-modality or rule-based clinical models indicate that multimodal AI models outperform biomarker-based stratification when it comes to predictive performance. The technological viability, validation levels, implementation environment, and user group all influence the significance of explainability in the CDSS. For AI to be realistically and widely used in multimodal cancer therapy and for personalized medicine to advance, these obstacles must be overcome.

KEYWORDS: Artificial Intelligence, Clinical Decision Support, Precision Oncology, Outcome Prediction, Data Security, Personalized Medicine.

1. INTRODUCTION

The field is being transformed by personalized cancer treatment known as precision oncology [1]. In order to tailor treatment to each patient's cancer, this paradigm shift encompasses genetic, molecular, and cellular investigations. Precision oncology selects the safest and most effective therapies to improve patient outcomes. This objective necessitates the use of artificial intelligence (AI) capable of aggregating and analyzing enormous amounts of complex, multimodal data beyond the capabilities of human beings. Genetic profiles, digital pathology images, medical imaging, and electronic health records (EHRs) can all be uncovered by AI (Fig. 1). This makes it possible to identify novel biomarkers and comprehend the biology of patient-specific diseases [2]. This technology has changed healthcare practice and has multiple applications. Oncologists can use AI-powered clinical decision support systems (CDSSs) to help them identify lung nodules and predict how well a treatment will work. Advances in cancer research can be made through enrollment in crucial clinical trials and the ability to predict survival. Obstacles exist despite hope. There are numerous obstacles to overcome when integrating AI into clinical practice. Security of patient data is critical. AI ethics are constantly under investigation, including the possibility of treatment recommendation bias in training data sets. It is difficult to make the decision to allow human therapists to observe the AI system's decision-making process. To realize AI's transformative potential in individualized cancer treatment, these ethical and technical obstacles must be overcome [3]. The foundation for AI in the mid-20th century was laid in Turing's 1950 paper. The first versions were only used in medicine. By overcoming these limitations, AI was able to be applied to complex algorithms and self-learning systems in the early 2000s thanks to deep learning. AI-influenced medication development was made possible by this technical advancement (Fig. 2) [4].

AI is extremely beneficial to cancer research. Real-world applications rather than theoretical models are used in cancer treatment. The classification of imaging data for the purpose of prediction and pattern identification was one of the early applications. Real-time AI improves colorectal polyp and lung nodule detection. AI improves pathological disease insights by integrating histology, imaging, and genetic data [5]. AI has significantly advanced cancer research. It might make it easier to enroll in cancer clinical trials and make decisions faster. AI develops into a potent technology that has the potential to enhance human comprehension, enhance diagnostic accuracy, and personalize cancer treatment. AI's role in precision oncology, particularly multimodal data fusion to enhance therapy and outcomes, is emphasized in this paper. In the diagnosis and prediction of colorectal polyps and lung nodules, AI systems perform better than physicians. It also addresses issues of data privacy, bias, and transparency in clinical decision-making as well as AI-driven clinical trial process optimization [6].



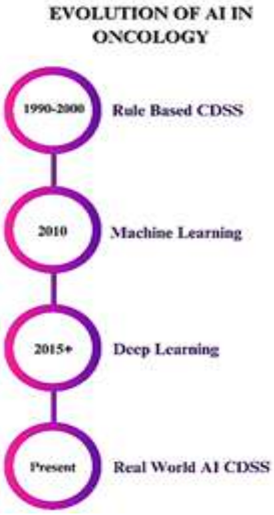


Figure 1: The precision Oncology framework. Figure 2: Oncology AI evolution.

2. FUNDAMENTALS OF CLINICAL DECISION SUPPORT SYSTEMS (CDSS)

A. Definition and types of CDSS

A Clinical Decision Support System (CDSS) helps health care workers make good clinical judgements by supporting their cognitive processes. They provide clinical recommendations, warnings, and other knowledge-based assistance by combining complex algorithms, patient-specific data, and a substantial body of medical knowledge [7]. Contrary to earlier models, CDSS models can now handle complex algorithms and learn from existing data sets thanks to AI and deep learning. Because of this one-of-a-kind property, it is frequently used in clinical practice to improve diagnostic accuracy, workflow efficiency, and prognostic risk [8].

- Real-time detection systems: The systems are intended to operate alongside current tests or procedures. During endoscopic therapy, a computer-aided method can detect colorectal neoplasia in real time. Improved diagnostic fidelity can result from these tools' ability to quickly identify anatomical regions that clinicians may overlook but are crucial to clinical care.
- Diagnostic and classification systems: The radiological images and patient data analyzed by this CDSS are used to aid in the diagnosis or nomological classification of serious illnesses. Examples include AI-based methods for evaluating pulmonary nodules using CT images for lung cancer screening and brain glioma classification using data from magnetic resonance imaging [9].
- Treatment recommendation systems: The best treatment for a patient can be selected by professionals thanks to these systems. This is accomplished through in-depth patient data analysis, extensive medical research, and best practices. By reducing clinical information overload and improving therapeutic options, CDSS supports clinical cancer therapy recommendations.
- Patient-Triage and risk assessment systems: In urgent or high-risk situations, a CDSS can also be used to quickly identify and prioritize patients according to clinical condition. An important illustration [10].

B. Evolution from ruled based to AI-driven CDSS

- early rule-based systems: Clinical Decision Support Systems (CDSS) have moved from rule-based models to AI-based structures. In the beginning, these systems followed predetermined rules and instructions for computation. Although they could help direct clinical decisions, their ability to analyze data and offer assistance was limited by the rules they were programmed with. They were hard to scale because adding new medical information or accommodating unusual clinical circumstances required a lot of human recoding. In some cases, these outmoded approaches were inapplicable in medical settings that defied their logic because they were too restrictive [11].
- Capabilities of modern AI-driven CDSS: As a result, AI-driven CDSS has become increasingly used in clinical practice for a variety of purposes, including improving diagnosis accuracy by analyzing imaging, genomic, and clinical history data. By automating common actions and presenting contextual information more quickly than before, they speed up procedural workflow. These methods go beyond diagnosis to estimate prognostic risk in order to predict long-term patient outcomes and aid in the completion of individualized treatment plans. The CDSS has grown from a simple tool to a powerful tool for improving numerous aspects of medical care [12].
- Data sources in oncology decision support: In the context of cancer, efficient Clinical Decision Support Systems (CDSS) require the integration of numerous, intricate data sources. Genomics data reveal patient genetic profiles by detecting mutations and indicators that affect illness development and therapy response. Precision oncology systems use multimodal data to create therapy and prognosis recommendations. Medical imaging data and a towel sample are provided by radiology and histology [13]. These visual data aqueducts must be examined by digital and computational pathology and ultramodern imaging for complaint classification and staging. Clinical data, which includes information about a patient's medical history and symptoms, also provide a contextual subcaste. The CDSS is able to fully comprehend the situation because these data are typically combined into EHRs as a single repository. AI systems can move from a single person to a detailed analysis thanks to the continuous integration of so many different data sources. Table 1 [14].

Table 1: Types of data for Oncology decision support.

Data Source	Applications	Strengths	Limitations
Radiomics	Tumour phenotyping from CT/MRI images	Non-invasive and enables longitudinal monitoring	Highly sensitive to acquisition variability

Pathomics	Histopathology image analysis	Captures tumour heterogeneity	Requires digital pathology workflows
Genomics	Mutation profiling	Identifies actionable therapeutic targets	Expensive and uneven availability
Transcriptomics	RNA-seq for immune signature analysis	Provides dynamic insight into tumour activity	Batch effects and complex standardization
Proteomics	MS-based biomarker discovery	Reflects the functional state of tumours	High technical variability
Clinical Data	Electronic health records, demographics, laboratory reports	Contextualizes molecular and imaging findings	Fragmented and non-standardized datasets

3. ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN PRECISION ONCOLOGY

A. Machine learning approaches

Precision oncology, a paradigm shift in cancer treatment that employs individualized and efficient strategies, has been made possible by AI and data-driven learning [15]. The central AI topic of machine learning (ML) is the focus of this frame. Data is used by machine learning algorithms to find intricate patterns and make predictions or classifications based on data. Machine learning (ML) models "learn" the guiding principles from massive, diverse datasets rather than following well-defined rules. Ultramodern cancer care generates massive volumes of data that must be analysed and interpreted [16].

- Multi-Modal data and clinical impact: These databases may contain patient-specific data from radiomics, genomes, proteomics, and electronic health records. Machine learning aids physicians in better comprehending a patient's illness and making better decisions [17] by examining multi-modal data streams.

4. APPLICATIONS OF AI-DRIVEN CDSS IN PRECISION ONCOLOGY

AI-driven CDSS is a component of the development and implementation of precision oncology. They give doctors cutting-edge tools to improve their skills and treatment methods. The limitations of experiment-based clinical reasoning are removed by these systems, which are able to seamlessly incorporate and evaluate enormous data sets that are diverse [18]. When quick and precise decision-making improves patient outcomes, high-stakes clinical settings are where their value is greatest. Oncologists may comprehend and integrate patient-specific genetic profiles, clinical trial data, real-time physiological signals, and more using these cognitive enhancers. A crucial step toward data-informed, evidence-based medication practice is putting these tools into use. The previous section explains how these systems are used for early detection and detection of cancer risk [19].

A. Cancer risk prediction and early detection

AI is able to analyze a lot of clinical, genetic, and lifestyle data on a large scale to find people at high risk and catch cancers earlier, making them easier to treat. Using patient history, imaging, biomarker profiles, or AI models, AI models may discover subtle trends that traditional methods miss, allowing for prompt intervention and proactive screening [20].

- Identification of high-risk individuals: In the field of oncology, one of the most important ideals is the early detection of cancer and the identification of people who are more likely to develop it. Through the comprehensive conflation of multimodal data, AI-enabled CDSS are uniquely suited to address these objects.
- Machine learning for risk vaticination: Longitudinal case data, including demographics, lifestyle variables, genetic features, and entire electronic health records, are used to extensively train threat prediction machine learning models like Random Forests and Support Vector Machines[21]. By combining complex and subtle non-interactions between remote variables, these algorithms may be able to generate a probabilistic risk score for particular types of cancer. This prophetic ability precisely positions sick groups. As a result, it is now possible to carry out visionary, strictly acclimatized webbing protocols and specialized preventative measures for individuals who pose a risk. Based on a case's inheritable labels and domestic medical history, a CDSS may recommend routine mammography or colonoscopy [22].
- Deep learning for early cancer discovery: Moreover, CNNs and other deep learning models are

required for medical imaging-based early cancer diagnosis. These computers learn from large picture libraries like mammograms, CT scans, and pathology slides to find and emphasize subtle irregularities and troubling characteristics that humans might overlook. These models aim to speed up clinical workflow, reduce radiologists' and pathologists' inter-observer variability, and improve webbing program sensitivity and specificity [23].

B. AI guided radiomics and pathomics for treatment planning and response

High-dimensional quantitative information on cancer heterogeneity, morphology, and microenvironment, which is crucial to therapy response, is provided by radioomics, features retrieved from CT, MRI, and PET. By identifying phenotypic imaging features associated with genomic and molecular characteristics, machine learning and deep learning models, particularly CNNs, trained on these imaging features can predict sensitivity to chemotherapy, radiotherapy, and immunotherapy[24]. Pathomics complements radiomics by revealing cellular and tissue-level cancer structure, immune cell infiltration, and proliferative patterns through digital processing of whole-slide histopathology images (Fig. 3). AI combines radiomics and pathomics to improve treatment response and prognosis prediction, making it possible to personalize treatment planning and enhance therapeutic strategies, like identifying patients who respond to immunotherapy [25].

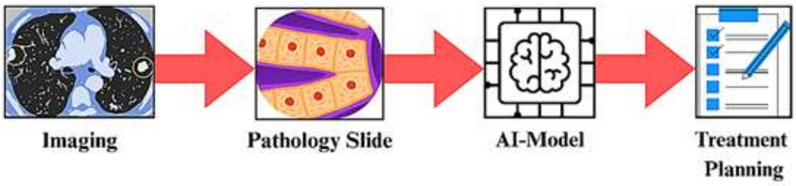


Figure 3: Workflow for Pathomics and Radiology.

C. Prediction of toxicity and clinical impact through the response

AI has in advance predicted therapy response and toxicity, two crucial parameters in cancer treatment. Excretion biology and case heterogeneity may be underestimated by conventional clinical and pathological indices. With the help of radiomics, pathomics, genomes, and clinical data, AI can create delicate, individualized prophetic models [26].

5. INTEGRATION OF MULTI-OMICS AND CLINICAL DATA

Because cancer is so diverse, no single biological dataset can adequately represent its complexity. Tumor behavior and therapeutic outcomes are influenced by genetic alterations, gene expression patterns, protein dynamics, and patient-specific clinical variables. For a better understanding of the causes of complaints and customized therapy planning, it has become critical to integrate multi-omics data with clinical data (Fig. 4)[27].

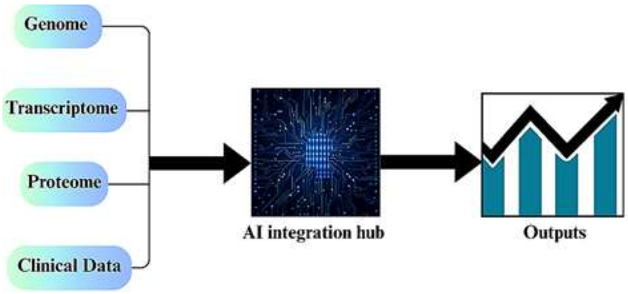


Figure 4: Multi-Omics integration model.

D. Application and challenges

Pathology can reveal aggressive characteristics, imaging can reveal tumors that cannot be surgically removed, and clinical history can provide therapy contraindications. Oncologists can select treatments based on this information to ensure each patient's safety and effectiveness. Although combining these disparate data aqueducts is challenging, the advantages are clear. Standards for reporting, insufficient data, and imaging and pathology procedures could limit their community [28].

6. REAL- WORLD CASE STUDIES

A. IBM Watson for oncology

One of the most prominent examples of cancer care cognitive computing is IBM Watson for Oncology (WFO). 5). WFO was created with Memorial Sloan Kettering Cancer Center to look at a lot of patient data, research papers, and clinical recommendations to find therapies that are supported by evidence[29]. Numerous difficulties and flaws prevented its practical application, despite its lofty objective. Because it was primarily based on U.S. standards, the First WFO had to adapt its instructions to local practice patterns, medication availability, and infrastructure in outreaches and local policy regulators of other nations. Second, it took a lot of resources to update the system's knowledge base to reflect the rapid change in oncology. Thirdly, doctors struggled to comprehend Watson's suggestions and place their trust in the system's interpretability. IBM Watson for Oncology's therapy advice function requires population-specific validation [30] due to the high concordance (80-96%) with multidisciplinary tumor board recommendations for breast, lung, colorectal, and ovarian cancers.

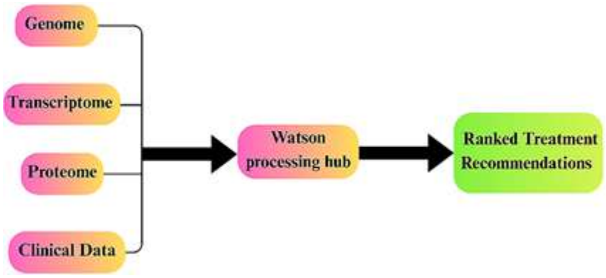


Figure 5: IBM Watson for oncology Workflow.

B. AI-Enabled clinical trials in precision oncology

The foundation of research is the design of traditional cancer trials, which typically have sluggish patient enrollment, restricted eligibility criteria, and inadequate patient representation. In precision oncology, AI has made it possible to improve clinical study design, performance, and analysis. Patient stratification and recruitment are aided by AI. Utilizing electronic health records (EHRs), molecular profiles, and imaging data, AI is able to assess patients for more complex eligibility criteria than humans. It increases the number of people who are most likely to benefit from targeted medicines and speeds up recruitment. As evidence accumulates, AI enables real-time adjustment of treatment arms and eligibility criteria [31].

C. Academic and industry collaborations driving AI-CDSS

Due to collaboration between academia and industry, AI-CDSS adoption in oncology is accelerating. Industrial partners offer regulatory and computational infrastructure expertise, while academic partners provide application area expertise, patient cohorts, and methodological innovation. Large-scale project execution is made possible by this.

7. OVERALL CHALLENGES AND LIMITATIONS

A. Data privacy and security challenges

Privacy, security, and moral issues arise when multi-omics, pathomics, and radiomics data are used in therapeutic decision-making. Concerns about re-identification, data breaches, and the misuse of sensitive patient information arise as a result of the extensive sharing required to train and test AI models. Despite the fact that compliance with GDPR and HIPAA is essential, international sharing is challenging due to variations in jurisdiction. Data safety is important. Using cloud services with access control and encryption, imaging and genomic data must be securely stored and transmitted. Patient trust and the institution's reputation could be jeopardized by these system flaws [32].

B. Algorithm bias and generalizability issues

Database bias and algorithm generalisability issues plague AI-based healthcare decision support systems. The data that AI models are trained on are important, and if these datasets favor particular demographics, institutions, or imaging techniques, their clinical predictions may not be accurate. AI bias may result in unjust recommendations and disparities in cancer treatment due to underrepresented demographics, disease incidence, or variations in imaging and sequencing technology [33].

C. Regulatory and legal frameworks for AI in oncology

Laws and regulations on AI in cancer care require strong executive control for patient safety, accountability, and AI trust. Because their responses are not entirely interpretable, data-driven, learning AI systems face distinct challenges in comparison to conventional medical equipment. Standards for AI-driven medical devices are being developed by regulatory bodies like the FDA and EMA. Important considerations include clear documentation of training sets, careful selection of performance metrics, and routine replication on various patient populations. Establishment-based certification procedures may be disrupted by regulating "adaptive" algorithms, which learn new methods and can change after approval.

8. FUTURE DIRECTIONS

By replacing static, rule-based recommendations with continuously learning, data-adaptive models that combine multimodal clinical, molecular, and imaging data, AI-driven clinical decision support systems will transform precision oncology. Clinically and more accurately, AI-enabled CDSS can predict patient-specific therapy response, toxicity, and disease trajectories. Table 2

Table 2: Application in Oncology: Rule-Based versus Metrics for CDSS Performance Enabled by AI.

Functional Area	Data Modality	Conventional Rule-Based CDSS	Performance Metrics of AI-Powered CDSS
Thoracic cancer screening	Chest CT	Size thresholds; manual radiologist scoring; limited sensitivity to subtle nodules	CNN-based models: AUC 0.87–0.94, Sensitivity 85–94%, Specificity 82–90%; performance comparable to expert radiologists
Breast cancer screening	Mammography	BI-RADS rule-based categorization; inter-observer variability	Deep learning models: AUC 0.89–0.94; Sensitivity 86–90%; reduced false positives compared to radiologists
Early identification of colorectal cancer	Live colonoscopy video	Visual inspection guided by heuristic rules	Real-time CNN systems: Sensitivity 91–99%; adenoma detection rate improved by ~14%
Molecular stratification of brain tumours	MRI	Manual radiologic interpretation; indirect genotype inference	CNN/radiomics models: AUC 0.84–0.92 for IDH mutation prediction
Forecasting efficacy of immunotherapy	CT radiomics + pathology	Biomarker-driven rules such as PD-L1 cut-offs	ML-based radiomics/pathomics: AUC 0.78–0.88; captures tumour heterogeneity
Pathology-based cancer diagnosis	Whole-slide pathology images	Manual histopathological grading; subjective interpretation	Vision-language foundation models: AUC 0.90–0.97 across diagnostic tasks
Multimodal oncology decision support	Clinical factors, imaging, pathology, genomics, EHRs	Isolated rule-based modules with limited data fusion	Multimodal foundation models: 5–15% AUC improvement compared to unimodal models
Surgical risk prediction	EHR and clinical variables	Static risk calculators with limited personalization	ML-based CDSS: AUC 0.82–0.90; reduced postoperative complications

- Federated learning and privacy-preserving AI: AI for cancer will advance if it can meet regulations regarding patient data privacy while also solving big data and diverse data problems. Federated learning (FL) lets institutions train models without sharing raw data, protecting privacy and minimising regulations. Re-identification dangers are reduced by safe multiparty computing, differential privacy, and homomorphic encryption. Safe and collaborative AI development is made possible by any one of these methods. Issues with clinical interpretability, computing resources, and technological standardization are all present in federated models [34].
- Integration with digital twin technology: Digital twin technology, a data-driven, virtual replica of a patient, is emerging in precision oncology. In precision oncology, digital twin technology can be used to simulate personalized treatments in real time, cut down on expensive trials, and encourage cancer treatment sustainability. By combining various types of data, such as genomic, imaging, pathological, and clinical information, these digital twins are able to simulate the progression of a disease and make real-time predictions about how well a patient will respond to treatment. These models can also be updated in real time thanks to the AI, allowing doctors to virtually test proposed treatments before

deciding which one to implement. The optimization of therapy adaptation, the prediction of toxicity, and individualized monitoring are all potential applications. However, ethical governance, biological fidelity, and data integration remain issues. Although the application of AI to digital twin models may not be the same for oncology, it may aid in personalized or dynamic decision support.

 Real-Time adaptive decision support systems: Dynamic real-time adaptive decision support systems (DSS) that change with the patient's clinical course are becoming more common in precision oncology. In contrast to static models, adaptive DSS utilize longitudinal data like serial imaging, pathology updates, laboratory results, and therapy response to update predictions and recommendations. Such programs provide personalized toxicology management, early relapse diagnosis, and therapeutic change in real time. In addition, they learn how to operate medical therapies using multimodal inputs and depart from predetermined treatment strategies. Major obstacles include seamless EHR integration, thorough clinical validation, and physician confidence in outputs that change quickly. However, the foregoing factors are insufficient and inefficient for DSS development. Real-time adaptive DSSs are necessary for responsive, data-based oncology diagnosis and treatment due to the dynamic nature of cancer. A colorectal cancer surgical decision support tool based on an AI-based risk prediction model was successfully implemented by Rosen et al. This study shed light on key requirements for AI-CDSS translation into clinical practice and provided a practical path from development to real-world deployment, minimizing postoperative complications..

 Patient-Centred AI in oncology care: This shift toward AI that is focused on the needs of the patient recognizes that the technology should be tailored to the needs, preferences, and values of each patient. By making complicated data easier to understand for patients and caregivers, AI can improve diagnosis accuracy, treatment planning, and collaborative decision-making.

Individualized risk prediction, treatment visualization, and the incorporation of patient-reported outcomes into routine care are made possible by these algorithms. Patients can participate in their treatment thanks to AI-enabled monitoring technologies and mobile health platforms that keep the clinic-to-home loop open. In patient-facing apps, equity, digital exclusion, and patient privacy persist. By making patients partners rather than recipients, patient-centered AI may improve oncology's responsiveness, transparency, and cooperation.

9. CONCLUSION

By combining clinical observations, pathomics, proteomics, genomics, and radiomics into a single platform for cancer patient stratification, AI-based clinical decision support systems (CDSS) are revolutionizing precision oncology. AI-powered systems may improve early detection, tumor staging and classification, medication treatment response and toxicity, and rule-based procedures. For global, patient-specific decision-making, their new multilayered molecular and data analysis surpasses previously unheard-of analyses. Through case studies, industry–academic collaborations, and AI-enabled clinical trials, this paper examines the technical depth of AI in cancer and its implications for clinical translation. It doesn't see AI as a disruptor but rather as a constant partner in the multidisciplinary treatment of cancer. More adaptable, transparent, and inclusive cancer models are made possible by explainability, regulatory terrain, common data standards, physician adoption, and new methods like federated learning, digital twins, real-time adaptive systems, and patient-centered AI. Multi-omics complexity and clinical significance may be linked by AI-CDSS in precision cancer, allowing for more precise, justifiable, and individualized treatment options. Finally, this can only be carried out with the help of multidisciplinary collaboration, thorough validation, and ethical safeguards. When used correctly, AI-CDSS has the potential to improve patient outcomes, reduce disparities, and usher in a new era of tailored cancer care.

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