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Distributed intelligence in cancer care: A systematic review of Cloud-Based oncology solutions

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Abstract

Cancer has been a major global health problem, causing more than one in six deaths and resulting in a significant amount of non-communicable disease mortality. To achieve effective cancer care, healthcare IT systems must be integrated, and data-intensive decision-making relies upon collaboration between different disciplines, which is hampered by segmented healthcare IT. With the advent of high-through technologies and cloud computing, new opportunities are opened for managing oncology-related big data. In this paper, a systematic review is explicitly presented of distributed intelligence (DI) systems in oncology that employ cloud-based platforms for improving the performance of cancer diagnosis, treatment, and research. The study extensively applied a PRISMA-guided methodology. It screened publications from 2015 to 2025 from Google Scholar, Scopus, and Web of Science, of which 18 high-quality studies were taken into analysis. The review then presents a taxonomy of cloud-based DI systems in oncology based on its architecture, its enabling technologies, and the clinical application domain. Additionally, it investigates the practicality of improving scalability and interoperability and, with it, the process of making a clinical decision, as well as the main challenges of implementation, such as data privacy, system integration and workflow complexity. This paper concludes by discussing future research directions to enhance AI-based cloud solutions for the delivery of comprehensive cancer care.

Keywords: Cloud solutions, Oncology, Distributed intelligence, Clinical decision support systems, Artificial intelligence

1.Introduction

Nearly one in six deaths (16.8%) and one in four deaths (22.8%) from noncommunicable diseases (NCDs) globally are attributable to cancer, making it a significant social, public health, and economic issue in the twenty-first century. Cancer ranks among the top three causes of death for individuals aged 30 to 69 in 177 out of 183 countries and is responsible for 30.3% of all premature deaths from NCDs worldwide [1]. The treatment of cancer requires multi-disciplinary care that handles significant volumes of healthcare information across different facilities through collaborative provider networks [2]. Early detection methods and precise treatment options show the potential to enhance cancer treatment [3], but clinicians face difficulties accessing medical records [4]. Healthcare IT systems that follow traditional approaches fail to satisfy medical needs because of their restricted hardware capacities, along with expensive operations, inadequate staff, and complications with secure data distribution [5].

The development of high-throughput technologies allows hospitals to store vast amounts of data at affordable prices, thus advancing oncology treatment and research towards a big data framework [6]. The cloud environment provides an optimal system for managing oncology big data while it enables scalable and efficient storage along with data sharing and analysis for oncology [7]. Cloud-based infrastructure systems provide accessible and affordable methods to manage large quantities of fast-moving, diverse cancer data [8]. The dispersed nature of these systems enables immediate data operations as well as instantaneous information exchange and integrated care coordination between institutions [9]. These systems prove vital for healthcare organizations to manage medical information along with medical images and complete treatment backgrounds [10].

This paper presents a comprehensive and organized idea known as distributed intelligence for oncology,

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considering the growing exploration of technological advancements for possible uses of Artificial Intelligence (AI) in oncology [11]. With the goal of advancing cancer prevention, screening, early diagnosis, and precision therapy, distributed intelligence for oncology is a cross-disciplinary specialty that combines oncology, radiology, pathology, molecular biology, multi-omics, cloud computing, and artificial intelligence [12]. Rapid advancements in AI technologies, including computer vision, machine/deep learning, natural language processing, and cloud computing, have made distributed intelligence for oncology possible [13]. We are confident that distributed intelligence will be crucial to the development of basic, translational, and clinical oncology in the future, even though the ideas and applications of this field are still in their infancy and face numerous obstacles and difficulties [14], [15].

This paper conducts an extensive systematic investigation of modern Distributed Intelligence (DI) systems that operate in cancer care. The research explores effective ways that distribute computing and intelligent systems inside cloud-based oncology platforms which support clinical teams and oncology care providers when making time-sensitive collaborative treatment decisions. The paper's essential contributions involve the following points:

- Develops a classification system for distributed intelligence systems that operate through cloud platforms in the medical field of oncology. This taxonomy organizes present solutions into three parts, including architecture description, technological enablers, and clinical application domains.
- Evaluates distributed intelligence integration for cancer care by demonstrating its capabilities to enhance scalability, enable data sharing, and improve decision-making support.
- Evaluates the main barriers to deploying distributed intelligence systems for oncology, which appear during implementation while addressing complex clinical workflows and sensitive data requirements.

Explores vital research areas and technology deficits within oncology decision support systems to direct innovative development of cloud-based applications.

This paper follows a systematic review methodology that contains section breakdowns. Section II describes the step-by-step methodology that was adopted to conduct this systematic review. Section III discusses the current research findings on distributed intelligence systems that operate through cloud platforms in the medical field of oncology. Section IV explores the limitations of deploying distributed intelligence systems for oncology and the future directions for the implementation of AI-based cloud solutions for cancer care. Section V concludes this review.

2. Methodology

An approach developed according to the PRISMA framework served to evaluate publications regarding cloud-based oncology solutions using artificial intelligence for cancer care. The systematic process included four distinct phases. Figure 1 shows the PRISMA diagram for this systematic review.

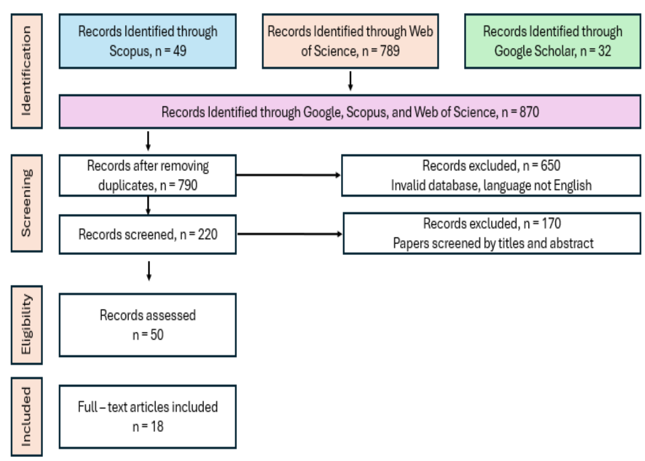

Figure 1. The PRISMA diagram for this systematic review

2.1 Identification stage

Three database platforms were used, including Google Scholar, Scopus and Web of Science, to obtain a wide selection of suitable publications. The search was conducted on 25 February 2025. The articles were included from the previous 10 years, i.e., Feb 2015 to Feb 2025. 32 records were found in Google Scholar, while Scopus yielded 49 results, and Web of Science produced 789 results, leading to a total number of 870 studies. The duplicates were removed which resulted in a total of 790 unique papers remaining for continuation. The complete search string for three databases is given below: ("distributed intelligence" OR "distributed computing" OR "cloud computing" OR "cloud-based solutions") AND ("oncology" OR "cancer care" OR "cancer treatment" OR "oncology care" OR "tumor treatment") AND ("machine learning" OR "artificial intelligence" OR "AI" OR "predictive analytics" OR "clinical decision support systems" OR "CDSS") AND ("data integration" OR "interoperability" OR "privacy" OR "security" OR "scalability" OR "performance" OR "resource optimization") AND ("healthcare" OR "healthcare systems" OR "medical records" OR "electronic health records" OR "EHRs") AND ("cloud-based" OR "cloud architecture" OR "cloud storage" OR "cloud services" OR "cloud infrastructure")

2.2 Screening stage

The Screening Stage led to the elimination of unrelated studies following the established inclusion and exclusion criteria specified in Table I and II. A total of 650 publications received exclusion, indicating 80 duplicates, 30 in other languages other than English, 5 from other sources, 5 with database entry errors, 10 without full-text access, and 520 not relevant to the review. The remaining records proceeded for further evaluation.

Table I. Inclusion criteria

Sn.	Attribute	Description
1	Relevance	Papers must directly address distributed intelligence or cloud-based solutions in cancer care
2	Focus	Papers should specifically explore or evaluate the implementation of cloud-based oncology solutions.
3	Type	Only peer-reviewed journal articles and conference papers were included
4	Diversity	Papers from all geographical regions and perspectives were included

Table II. Exclusion criteria

Sn.	Attribute	Description	Excluded
1	Focus	Exclude all papers on distributed intelligence or cloud-based solutions unrelated to cancer care. Also, exclude papers that discuss oncology but lack any focus on distributed intelligence or cloud-based solutions.	510
2	Language	Exclude all papers published in languages other than English to ensure accessibility and uniformity in analysis.	30
3	Sources	Exclude all non-peer-reviewed sources such as websites*, blogs, and opinion pieces to maintain the academic rigor of the systematic review.	5
4	Duplicates	Exclude duplicate publications or papers that substantially overlap in their content to maintain diversity and originality.	80
5	Type	Exclude non-technical papers lacking depth or not contributing to research on distributed intelligence or cloud-based oncology solutions.	10
6	Completeness	Exclude publications whose content is incomplete, inaccessible, or invalid due to database errors.	15

2.3 Eligibility stage

A detailed study was conducted against the remaining 220 publications, where researchers analyzed their titles and abstracts and assessed their methodological quality. 170 publications were excluded at this stage. A total of 170 publications were eliminated during this stage through the review process, including 150 irrelevant titles for cloud-based oncology solutions, and 20 more publications dropped after abstract screening failed to match the research inquiries. A total of 50 articles passed the stage evaluation to proceed with full-text assessment.

2.4 Inclusion stage

The researchers assessed the entire text of 50 publications during the inclusion stage to confirm their methodological quality and relevance. The research ended with 18 high-quality studies that survived all criteria for inclusion.

3. Research findings

The research findings from the final set of articles are as follows:

3.1 Architecture description of Cloud-Based solutions for oncology

3.1.1. Centralized vs. decentralized cloud computing

In the evolving landscape of cloud-based healthcare solutions, centralized cloud computing has become a dominant model, particularly in handling large-scale medical data and improving interoperability across healthcare organizations [19], [20]. Centralized cloud computing consolidates computing resources including storage, processing, and applications within central data centers. These systems support scalable and flexible operations, as seen in frameworks hosting EHRs across nationwide healthcare facilities using HL7 protocols [21]. Centralized models have demonstrated utility in diverse oncology-relevant use cases, such as integrating EHRs from multiple institutions, deploying private clouds in rural settings for improved latency, and developing unified clinical interfaces through SMART-on-FHIR [22], [23]. However, these systems face challenges in terms of data privacy, network latency in rural areas, and cost, especially when dealing with sensitive oncology records or implementing sophisticated security like biometric authentication or audio file storage [24], [25].

On the other hand, decentralized cloud computing represents an emerging paradigm shift, particularly relevant to distributed intelligence applications in oncology [26], [27]. By distributing data storage and computational tasks across multiple nodes or devices, decentralized systems offer improved resilience, reduced bottlenecks, and enhanced privacy through localized data control [28], [29]. For example, a decentralized campus health system used personalized storage pods to allow parallel processing and reduced latency while maintaining strong privacy protocols [30]. In the context of oncology, such models may empower patient-centered care by enabling secure, localized storage of medical records on patient devices, facilitating real-time data sharing across multiple healthcare systems without centralized dependency [31].

Table III. The difference between centralized and decentralized cloud computing

Aspect	Centralized Cloud Computing	Decentralized Cloud Computing
Strengths	Scalable and flexible infrastructure Centralized Electronic Health Records (EHR) systems Standardized data sharing across institutions Efficient for big data analytics	Resilient to system failures Reduced network bottlenecks Enhanced privacy and user control No need for centralized infrastructure
Limitations	Risk of large-scale data breaches Network latency in remote or rural areas High setup and maintenance costs Biometric security implementation is expensive	Device-level security vulnerabilities Lack of enterprise-grade security features Inconsistent access control mechanisms
Usage in Oncology	Integrated oncology records across healthcare systems Nationwide cancer data repositories for research and policy Clinical data clouds supporting pediatric oncology	Localized, patient-controlled oncology records Mobile-based Personal Health Records (PHRs) Faster, local decision support for cancer care

3.1.2 Edge cloud computing

Edge-cloud computing, as an enabler of intelligence distribution, plays a crucial role essential for creating data processing assets near information entry points, hence reducing network delays and performing real-time data analytics that are critical for making oncology decisions [32]. Among four different medical purposes that the Internet of Medical Things (IoMT) supports are identity recognition, vital signs monitoring, remote patient monitoring and equipment management. This system is built on a wireless sensor network [33], which also provides biosensors, sensors and implantable sensors in ICUs, emergency rooms and operating theatres to monitor the patient's vital signs. The removal of operational barriers allows for the usage of wearable medical devices made of these sensors for continuous personalized health monitoring and treating expenses effectively [34]. This will implement the 5G technology which will expand the digital medicine applications with the mobile emergency services, remote consultations, and the surgical guidance because it brings more diverse medical big data sources [35], [36].

3.1.3 Microservices based designs

Microservices design architecture allows building modular, easily scalable, and interoperable systems by decomposing an extensive application into smaller, independent services that communicate via lightweight protocols [37]. This architectural approach plays a key role in integrating multiple machine learning-based inference systems in distributed intelligence for oncology to support complex clinical decision-making processes. As a result, the proposed software intergenerational architecture "μeHealth 4.0" intends to combine and connect traditional eHealth applications (based on a service-oriented architecture) and modern microservice-based systems capable of handling dynamic and heterogeneous data sources through proper metadata standardization [37]. μe-Health 4.0 differs from other models by advocating replicability, scalability and openness of specialized services as well as compatibility with several machine learning models like logistic regression, random forest and XGBoost to carry out tasks like prediction, monitoring, and treatment decision support. Although demonstrated in a use case of the prediction of intradialytic hypotension during hemodialysis, this architecture was created to have broad applicability to other medical domains, such as diabetes and colon cancer, which coincide directly with the goals of oncology-focused DIs [37].

3.2 Data flow and its components for distributed intelligence

The execution of an entire patient medical history depends on straightforward data integration between cloud-based oncology platforms and Electronic Health Records (EHRs) and genomic profiles along with radiological images and patient treatment outcomes [38]. Oncologists gain superior disease comprehension through the combination of multiple data sources, which provides them with a complete set of information needed for their treatments [39]. AWS and Google Cloud Healthcare operate as cloud platforms that make it easy to unite data streams from local hospital networks and research hub databases. Healthcare providers benefit from data source integration to obtain comprehensive patient information and achieve protected database-sharing capabilities to promote medical teamwork between different health facilities. Healthcare specialists from multiple domains achieve better medical diagnostic precision through cloud-based solutions, which also lead to more effective treatment strategies [40], [41].

3.2.1 Electronic Health Records (EHR) integration

The cloud platform unifies access to specific oncology EHR information which is distributed between multiple care settings and hospitals. The systems manage cancer patient data effectively while improving inter-disciplinary coordination and serving decision support needs from initial to final stages of cancer care treatment [41].

3.2.2 Medical imaging and diagnostics

The storage and processing, together with the safe sharing of massive radiology and pathology image files, occurs within cloud-based systems [42]. Through AI algorithm incorporation, they enable quick diagnostic services linked with high precision and minimize storage requirements for local IT systems [43]. Cloud-based medical imaging stands as a principal healthcare implementation in oncology practice. Three key targets of this approach are to enhance cancer diagnosis precision and team-based assessment across distant experts and to track therapy reaction patterns throughout time [44].

3.3. Transmission of data through secure pipelines

The transmission of sensitive medical data to cloud platforms in distributed systems of oncology is a foundational security concern in the realm of distributed systems of oncology. Because these systems require substantial robustness of both wellarchitected pipelines for managing the volume and complexity of multimodal data, alongside data security, data integrity and data interoperability, they rely ever more heavily on these systems. Secure pipelines generally rely on standardized APIs (Application Programming Interfaces), encryption mechanisms, default access control protocols, etc., to provide data flow management between on-premises environments and cloud services. For example, one study worked with the Google Cloud Healthcare Natural Language API to process almost 167,179 clinical trial text records [45]. Those records were sent securely to the cloud over APIs and subjected to entity extraction for genes, medications, and laboratory tests. In large-scale oncology informatics research with 77,702 API calls, the pipeline's security and reliability made it possible [45].

Moreover, these pipelines also support the dynamic needs of multimodal oncology datasets in design. Additionally, the MINDS (Multimodal Integration of Oncology Data System) system is based on a cloud-native architecture and leverages metadata frameworks and interoperable APIs to securely and scalable integrate different types of disparate data like radiological scans, histopathology images etc. [46]. MINDS uses auto-scaling infrastructure and tracks data provenance to enable security and transparency along the whole data lifecycle [46]. Similarly, AWS cloud services also provided the infrastructure for analysis of the microbiome dataset in which Amazon S3 stores encrypted data in the storage space and EC2 instances do the computations, and all this is managed through secure command line interfaces and encryption keys to ensure the patient data transfer and analysis is secured [47]. Altogether, these represent secure transmission pipelines and standardized APIs to allow distributed intelligence systems to operate effectively and safely within a cloud environment as we push the boundaries of precision oncology [48].

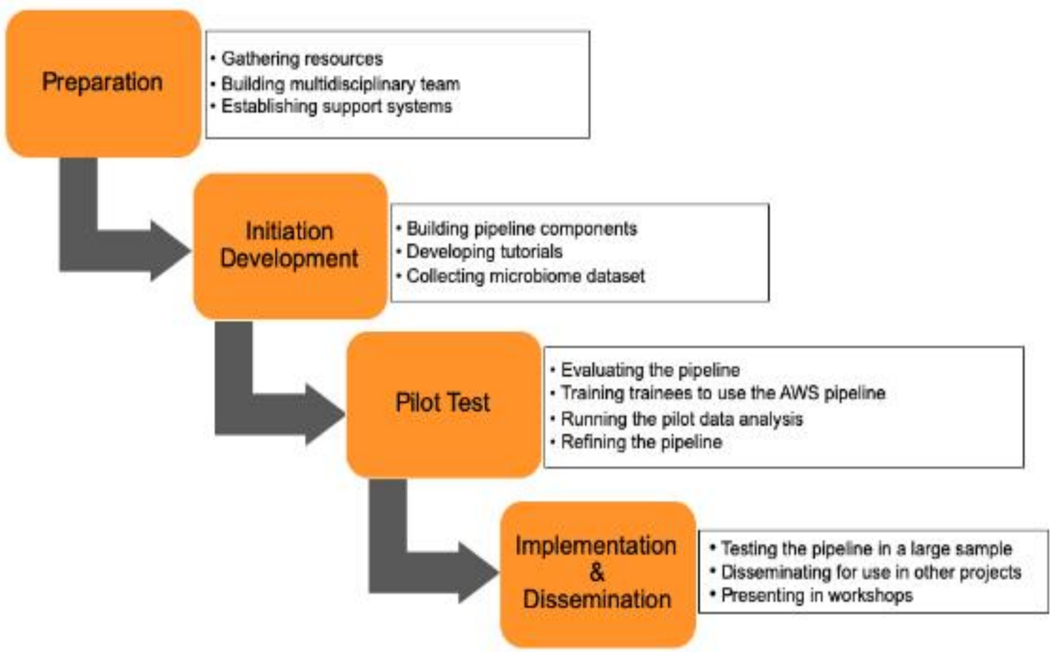

Figure 2. The data pipeline flow for developing distributed intelligence-based solutions in oncology

3.4 Technologies in distributed intelligence for cancer care

Modern distributed intelligence technology for oncology has improved cancer care by introducing cloud-based solutions. The medical analysis platform IBM Watson for Oncology functions as a cloud-based oncology solution that uses Natural Language Processing (NLP) and Machine Learning (ML) to conduct vast unstructured medical data evaluation

for delivering personalized treatment plan recommendations [49]. The deployment of distributed intelligence within oncological care combines three essential technologies, namely Artificial Intelligence (AI), Machine Learning (ML) and cloud computing, for transformational purposes.

3.4.1. Artificial intelligence and machine learning in oncology

AI functions together with ML to work as essential drivers of cloud-based oncology solutions development. Large datasets comprising genomic information, clinical histories, and radiological photos are analysed using these technologies to produce novel predictive models and biomarkers [50]. The use of deep learning, together with other ML algorithms, succeeds at finding patterns in imaging data to enable early cancer detection in breast cancer as well as lung cancer and colorectal cancer [51]. The deep learning model developed by Google's DeepMind Health permits eye scan evaluations to detect diabetic retinopathy and macular degeneration signs that could potentially be adapted for oncology diagnosis [52]. AI and ML systems for oncology discover optimal treatment methods through analysis of patient's individual genetic makeup and clinical conditions [52]. PathAI platform revolutionizes pathology operations by automating tissue analysis to boost diagnostic accuracy [53].

3.4.2 Predictive analytics in oncology

The distributed intelligent system turns predictive analytics into the most effective tool for cancer care delivery. Using current and recorded clinical data predictive models helps healthcare professionals create disease predictions about future illness developments while monitoring treatment results alongside safety risks [54]. AI predictive tools create models to assist healthcare professionals in better-understanding disease recurrence risk factors and metastasis properties for developing customized watch-and-treatment care programs for patients [55]. Predictive analytics has found its most prominent adoption through chemotherapy outcome management systems [56]. The genetic mutation analysis conducted by predictive algorithms in tools such as OncoKB Knowledge Base and Cancer Genome Interpreter leads to therapeutic analysis results [57]. Doctors who infuse genomic information as well as clinical data and imaging results into predictive computations will boost their treatment decision-making which results in superior patient survival statistics and elevated cancer patient lifestyle quality [58]. Predictive analytics functions as a vital tool in oncology care to enhance resource management efficiencies. Cloud-based medical systems help healthcare providers make better resource distribution decisions because of outcome prediction, which results in patients receiving prompt, suitable health care [59].

3.4.3 Data Security and blockchain in oncology

Medical information security and privacy protection expands as healthcare data becomes increasingly stored on digital cloud platforms [60. The newly emerging blockchain technology solves multiple health delivery problems in oncology [61]. Blockchain security provides protected healthcare data while stopping unauthorized modifications through its decentralized system, which allows for complete transparency in treatment and patient interaction records. The integration of blockchain technology with cloud-based oncology systems has the potential to establish secure interactive data management, which offers complete transparency of patient information [62]. Data stored in genomic format in cloud-based oncology platforms achieves protection by blockchain implementation that safeguards patient privacy and allows researchers and clinicians to access verified data. The visibility of identity protection, together with patient data usage permissions, receives enhancement through blockchain tracking systems [63]. Blockchain systems create secure data interchange paths between healthcare facilities by integrating forces with artificial intelligence and cloud-based technology applications. When patient data accuracy joins forces with blockchain security and transparency features, it increases trust in cloud-based oncology solutions, resulting in better decision-making efficiency [64].

3.4.4 Tele-Oncology & remote monitoring

Through cloud-enabled systems, doctors can provide telehealth consultations while performing remote patient monitoring for cancer care delivery [65]. The services prove valuable in restrictive medical settings as well as prolonged post-treatment monitoring by providing accessible care with continuous management for patients [66]. Modern telehealth solutions based on cloud are becoming fundamental for oncology practices that need remote monitoring and virtual medical sessions [67]. 9% of studies described cloud-based tele-oncology applications that enhance communication between patients and providers, boost diagnostic capabilities, and assess health status after hospital releases. Real-time monitoring of quality of ife and vital signs, along with artificial intelligence systems that deliver early breast cancer detection before building better patient treatment adherence methods, represent specific implementation cases [68]. The cloud-based infrastructure allows medical staff to deliver ongoing evidence-based care which extends beyond traditional healthcare arenas [69].

3.4.5 Interoperability

The creation of cloud-based distributed intelligence systems for oncologic care depends heavily on interoperability because it allows various healthcare technologies to communicate effortlessly [70,102]. All systems participating in oncology patient care successfully exchange meaningful patient information by using interoperability methods despite their separation across various medical data assets, including electronic health records (EHRs), imaging systems, laboratory platforms, and genomic databases [71]. The pursuit of standardization leads to two crucial tools called Health Level 7 (HL7) and Fast Healthcare Interoperability Resources (FHIR), which serve as essential frameworks. Standardized operational guidelines have been developed to organize health information during system-to-system transmissions, making patient care coordination and error reduction possible [71]. The main obstacles to cloud-based healthcare interoperability stem from non-unified standards alongside vendor-specific data formats and separate information systems [72]. Industry leaders work to establish uniform data models and promote open-source developments to remove barriers that stand between clinical and research excellence and create a connected information system [73]. Interoperability in oncology has advanced through the implementation of Minimal Common Oncology Data Elements (mCODE). Through the leadership of the American Society of Clinical Oncology, multiple stakeholders established mCODE as a standardized structured data system designed for oncology care with six domain sections [73]. mCODE specifies its data structures using HL7 FHIR standards to present a system for oncology data gathering and distribution between various healthcare platforms. The mCODE FHIR Implementation Guide has received HL7 approval which creates a major advancement towards seamless cancer data interoperability. CELR has shown its capability to enhance clinical workflow efficiency and cancer research while improving patient benefits through standardized and precise whole data availability for cloud-based AI applications. The complete utilization of distributed intelligence in oncology requires robust interoperability between systems which depends on frameworks including HL7, FHIR, and mCODE [73].

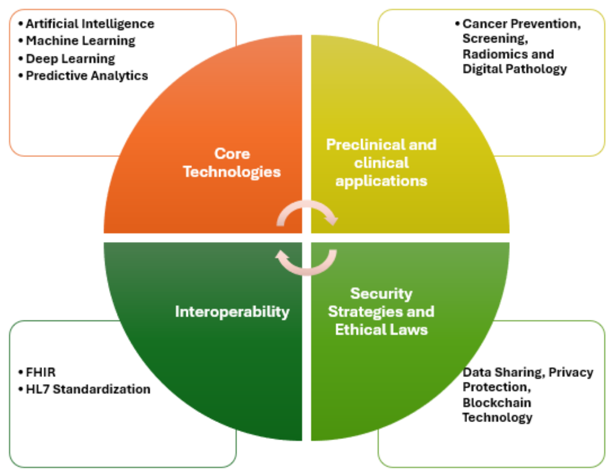

Figure 3. The essential technologies involved in the development of distributed intelligence-based systems in oncology

3.5 Clinical Decision Support Systems (CDSS)

Through cloud-based deployment CDSS platforms automatically detect real-time situations which alert users while they receive recommended treatments together with risk evaluation data for oncology patients [74]. Cloud-based distributed AI models improve both evidence-based medical decisions and maintain standardized clinical patient care [75]. Medical solutions built by machines through integration with cloud facilities now lead to the transformation of CDSS within oncological practice. The application of artificial neural networks (ANN) and support vector machines (SVM) and decision trees (DT) among other ensemble models such as XGBoost and random forest through cloud platforms contribute to cancer recurrence prediction in combination with survival and treatment response analysis [76]. The distributed AI models help healthcare professionals diagnose early and evaluate treatment risks and establish treatment protocols thus proving the effective combination of distributed AI with medical decision-making [77].

Real-time oncology systems combine statistical aggregated data to resolve data heterogeneity problems which makes possible interinstitutional collaboration through patient privacy protection [78]. Real-time oncology applications like Innovaccer Healthcare Data Platform unite multiple cancer datasets from disparate sources to deliver AI-based decision support immediately for health professionals [79]. Through this platform users have achieved notable healthcare improvements which have led to lower clinical expenses together with better treatment results for cancer patients. The platform's application across US medical facilities with millions of patient records at thirty different locations produced $11.5 million worth of savings per year alongside enhanced patient engagement results alongside better clinical performance results. Through its interoperable system and analytic automation, oncologists receive improved capabilities to make data-driven clinical choices that optimize resource management while delivering better healthcare outcomes to patients [80].

3.5.1 Mobile Distributed Decision Support Systems (MDDSSS) for oncology

Mobile Distributed Decision Support Systems (DDS) transform cancer care management through real-time execution by linking mobile devices with cloud-based distributed decision platforms [81]. This system allows oncologists, healthcare staff, and their patients to access medical information and diagnostic data and receive therapeutic advice at any moment from mobile terminals 81]. These systems provide maximum benefit to populations located in remote and underserved locations because they lack specialized cancer care standards [82]. The SMARTHEALTH system demonstrates how mDDSSs mainly serve cardiovascular disease management while offering the potential for cancer care delivery within resource-limited areas [83]. The system serves patients with cancer by delivering up-to-date, evidence-based treatment suggestions even when the local medical infrastructure remains restricted. mDDSSs serve medical applications by providing dynamic updates to health information and treatment protocol changes [83]. Healthcare providers can access instantaneous treatment findings through mDDSS technology from clinical research alongside current scientific developments, which helps deliver optimal medical care for cancer patients [81].

3.5.2 Multiagent Systems (MASs) in distributed oncology decision support

Autonomous intelligent agents use Multiagent Systems (MASs) as key components of cloud-based oncology decision support systems to enable collaborative decision-making [84]. The system incorporates agents who represent stakeholders from multiple sectors of oncology care, including healthcare providers and patients with their caregivers and oncologists who work to address complex cancer care challenges [84]. Oncology applications of MASs allow healthcare organizations to optimally utilize their resources while enhancing medical diagnoses and aiding therapeutic decision support at an individual patient level [85]. The Health Agents platform supports brain tumor classification tasks through MAS functionality that trains distribute datasets acquired from different healthcare institutions [85]. Secure model diagnostics become possible through a system based on decentralization which upholds privacy protection both for patients and their information [86]. MASs enhance cancer treatment plans by examining complicated datasets through pattern assessment that provides on-demand personalized care recommendations, which decreases diagnosis errors while accelerating clinical decision support [86], [87].

3.5.3 Collaborative Distributed Decision Support Systems (CODSS) for oncology

The Collaborative Distributed Decision Support Systems (CoDSS) function as platforms to improve real-time data-driven decision-making between teams working in cancer care [88]. AI-based cloud solutions with patient data and clinical records integrate through these systems to allow oncology treatment teams to operate together regardless of where they are located. Philips Precision Medicine Oncology represents a prominent CoDSS for oncology because it, by uniting different datasets, provides individualized treatment selections based on genetic mutation assessments along with tumor and patient background information [89]. This system allows oncology teams to collaborate at present, which enhances the reliability of their treatment choices, especially when treating complex cases involving multiple expert opinions [90]. The implementation of blockchain technology within CoDSS supports the resolution of security and privacy problems. The blockchain-based framework of CoDSSs provides secure decentralized patient data sharing that allows authorized personnel access, therefore maintaining HIPAA and GDPR compliance [91], [92].

4. Challenges and future directions

The deployment of distributed intelligence systems in cancer care presents various major obstacles which comprise data integration problems and privacy and security risks alongside scalability limitations and the complicated process of implementing artificial intelligence (AI) systems.

4.1 Data integration and interoperability

Cancer care systems work with many kinds of patient information, such as medical files, predictable results, genomic patterns and imaging reports. The achievement of consolidated cloud-based management for multiple data sources poses a substantial obstacle to modern electronic health initiatives [54]. The data originates from multiple heterogeneous systems, including Electronic Health Records (EHRs), radiology tools and pathology systems, together with wearable sensors, which operate with independent format and structure [53]. Systems require considerable interoperability work to harmonize differing data formats, so the information becomes usable for decision-support solutions. The lack of universal standards for data representation exacerbates this problem [62]. Genomic data follows separate representation patterns compared to imaging data and clinical notes, which hampers consistent processing of information between sources. The challenge becomes wider due to requirements for new data type standards, including real-time sensor data, while maintaining the adaptability and scalability of systems [94].

4.2 Privacy and security

Providing secure protection of cancer patient data emerges as a fundamental obstacle for cloud-based oncology solutions because of their sensitive nature. Such decentralized systems [26], which transmit patient information through various networks to cloud storage, cause multiple privacy and security risks regarding unauthorized access and noncompliance with health privacy regulations such as HIPAA and GDPR [64]. The main security challenge stems from patient data transport on networks particularly during wireless data transfer operations between IoT devices and sensors with cloud servers. Physician privacy requires protected data storage solutions and encryption protocols together with access control frameworks to secure patient information [62], [63]. The challenge exists in achieving health information privacy alongside the requirement for clinicians to receive real-time clinical decisions. The healthcare industry now focuses on developing solutions through end-to-end encryption roles-based access control, and privacy-preserving data architectures to resolve privacy concerns while maintaining data protection standards [64].

4.3 Scalability and performance

Vast medical and patient data sets handled by cloud oncology platforms require significant computational resources to process all information, including images and histories. Scalability stands as a significant issue because healthcare data volumes are expanding exponentially [94]. Implementation of advanced cancer care data analysis and multisource data integration contributes to increased strain on the functionalities of these systems. The effective expansion of cloud infrastructure to handle substantial datasets, along with the ability to conduct immediate analytics operations at their peak performance levels, stands as a critical obstacle [95]. The improvement of scalability depends on distributed data processing frameworks that incorporate Apache Hadoop and Apache Spark techniques [96].

4.4 Artificial Intelligence (AI) challenges

Cloud-based oncology solutions use AI and Machine Learning (ML) algorithms to provide predictive analytics personalized treatment plans, and early cancer detection features. Multiple barriers exist for implementing AI technology in distributed cloud systems [50]. The implementation of AI models faces significant challenges because they demand high computational power that limits their use on mobile phones and IoT nodes with restricted resources [51]. Deep learning algorithms, together with other AI models, require substantial computational power to achieve practical medical image analysis and genomic data interpretation [52]. The clinical practice demands AI models to produce decisions that healthcare providers can comprehend to maintain system trust. Users can understand AI model decision-making processes through the explainability method SHAP (Shapley Additive Explanations) after model execution [53]. These methods require excessive computational power that makes them impractical for real-time processing of large-scale data within cloud environments. Researchers focus on two leading solutions to address this problem: the development of interpretable machine learning models and the integration of explainability methods with deep learning capabilities to preserve transparency and trustworthiness [54].

4.5 Resource optimization and cost efficiency

Cloud-based oncology solutions operate through cloud infrastructure, yet the infrastructure costs increase when the system needs additional capacity [96]. The primary challenge arises from determining the optimal balance between resource distribution for cost efficiency and high-quality service delivery [97]. System performance remains unaffected when dynamic resource allocation teams up with elastic cloud services, which automatically scale computational resources based on demand requirements. The combination of distributed databases and data lakes in cloud-native storage solutions helps organizations reduce their future expenses for maintaining large datasets [98], [99].

Compared with 4G, 5G has the characteristics of high speed, low delay, wide connection, faster mobile speed, higher security and more flexible service deployment, which has brought a significant impact on the innovation of edge computing technology [100]. In addition, the combination of 5G and edge computing has laid a technical foundation for the development of smart medicine, especially telemedicine. Telemedicine, including remote consultation, remote surgery, and remote US, requires real-time ultra-high-definition image quality, medical image and other massive data transmissions, which also promotes the deployment and implementation of 5G + edge computing. At present, there have been successful cases of cross-domain remote precise operation control and guidance. “5G + edge computing” is of great significance to the subsidence of high-quality medical resources, the alleviation of uneven distribution of medical resources, and the reduction of patients’ medical costs. With the arrival of the 5G era and the continuous development of edge computing, the future of telemedicine means will emerge endlessly [101]. However, 5G also brings a lot of security problems, including security capacity opening, virtualization security, heterogeneous paradigm authentication and authentication, other native challenges, VR/AR content security, traditional security, data security and privacy protection and other application challenges, which are all worthy of study in the future [100].

5. Conclusion

The study carefully reviews the changing part distributed intelligence systems play in cloud-based oncology platforms to show their transformative power in cancer care delivery. Cloud computing, together with artificial intelligence, transforms traditional healthcare systems through real-time scalable solutions, which enable collaborative data management operations for oncology complexity. This study's developed taxonomy presents an organized system for assessing DI systems through both technical as well as clinical parameters. Promising progress exists, although several major obstacles continue to challenge projects, including secure information exchange, publishing proper clinical processes, and optimizing resource management. Further advancement of digital transformation in oncology care depends on solving identified system limitations. The future development of precision oncology will require the creation of interoperable ETH, locally based, and clinically examined DI systems. Through distributed intelligence systems, healthcare organizations worldwide can improve their defenses against cancer by enhancing prevention strategies, diagnosis probabilities, and individualized treatment delivery.

Author contributions

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D.K., H.D., and A.S.; Investigation, H.D. and A.S.; Resources, V.G., D.K., H.D., and A.S.; Data curation, H.D. and A.S.; Writing—original draft preparation, H.D. and A.S.; Writing—review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest.

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