

REVIEW

Interoperability of Electronic Health Records and Clinical Decision Support Systems: an architectural integration perspective

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Abstract

Electronic health records (EHRs) are huge, distributed systems, and usually use different and incompatible standards. Achieving seamless EHR integration is crucial for providing a comprehensive view of patient health and enabling collaborative use of data across healthcare systems. Interoperability, the primary mechanism for achieving such integration, has become a central research topic within the artificial intelligence and medical informatics fields in recent years. Beyond EHR–EHR exchange, interoperability is also required between EHRs and clinical decision support systems (CDSSs), as well as among different CDSSs. This paper presents a comprehensive review of recent research on interoperability in EHR and CDSS ecosystems, focusing on both data and knowledge interoperability. Current survey publications have addressed the idea of interoperability from a narrow perspective, such as standards and technologies, but there have not been any reviews that have looked at interoperability from an architectural integration perspective. This paper broadly reviews recent interoperability literature in data and knowledge interoperability domains. This review provides a background of EHR and CDSS systems and then discusses the different techniques, approaches, and standards to achieve interoperability in EHR and CDSS systems. A new interoperability classification is proposed, including (1) EHR-EHR interoperability, for the global integration within a single EHR system or among heterogeneous EHR systems, (2) CDSS-EHR interoperability, for the integration of EHR data and CDSS knowledge, and (3) CDSS-CDSS interoperability, for the integration of various CDSS knowledge bases. To our knowledge, no prior survey has examined these three dimensions of interoperability together. Achieving these levels of integration is expected to enable smoother EHR systems and facilitate modular, anonymous, and seamless integration of CDSSs within healthcare ecosystems.

Keywords Electronic health record · Healthcare data integration · Clinical decision support system · Standardization · Interoperability



1 Introduction

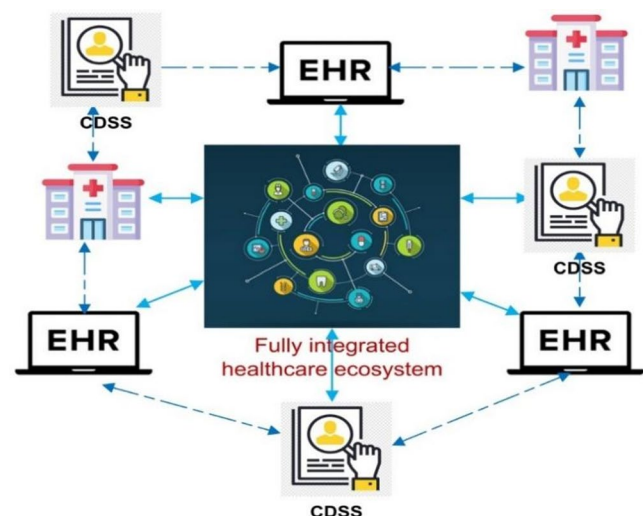
Electronic health records (EHRs) are repositories for patients' lifetime healthcare information [1]. They are patient-centered, longitudinal, and comprehensive systems [2]. Although EHR data are widely utilized for numerous objectives by patients, healthcare organizations, clinicians, and decision-makers, they are not owned by any single healthcare provider. Consequently, various efforts have been introduced to promote and expand the adoption of EHRs by hospitals and healthcare professionals [3]. The issue is that the majority of systems are built on heterogeneous architectures, some of which are unable to communicate with other internal and external medical systems. The ability of healthcare systems to understand, share, and coherently use EHRs is known as interoperability in the healthcare domain [4]. It guarantees a shared interpretation of medical information between various healthcare providers more quickly and accurately. Therefore, it could reduce medical errors [5]. According to HIMSS, interoperability has four levels: foundational, structural, semantic, and organizational [4].

The functions of EHRs go beyond just data storage. Clinical information can be reused to perform and improve several functions and capabilities, including patient healthcare assistance, reusing of data through health services management, reporting, clinical decision support, and epidemiological research [6]. Clinical Decision Support Systems (CDSSs) leverage EHR data to provide actionable insights that support diagnosis and treatment. A healthcare information system (HIS) is effective only when its components are integrated to deliver a comprehensive view of patient data at each encounter [4]. Therefore, it is evident that HIS is effective in the existence of integrated components for decision-making processes.

Healthcare data integration aims to combine healthcare data from diverse or distributed sources so that they can be processed as if originating from a single source. However, it has become urgent to combine different CDSSs into EHR ecosystems to provide real-time, accurate, personalized, and reliable assistance for physicians to manage different diseases. It has various complicated problems. In the past, doctors avoided using CDSS due to the “double data entry” requirement that impedes patient care. The double data entry problem has diminished as more CDSSs have been incorporated into EHR systems, although other CDSS systems are still standalone and not integrated into the EHR ecosystems. To solve this problem, interoperability techniques can be used to avoid data silos by ensuring data exchange [7]. As illustrated in Fig. 1, interoperability enables distributed EHR systems to operate as a unified ecosystem.

Despite its importance, achieving interoperability in healthcare remains a significant challenge. There is a limitation in the state-of-the-art of how interoperability could be used in the healthcare domain to enhance the integration, sharing, and exchange of healthcare information. Current systems often operate in isolation, creating data silos that hinder information sharing across EHR platforms and limit the effective use of CDSSs. Although

Fig. 1 Fully integrated healthcare interoperable ecosystem



several surveys have reviewed interoperability, they typically focus on narrow dimensions—such as technical standards, data formats, or semantic technologies [8–11]. As a result, the architectural integration perspective—that is, how interoperability can be designed and achieved across EHR–EHR, EHR–CDSS, and CDSS–CDSS systems—has not been comprehensively reviewed. This gap prevents healthcare providers and researchers from gaining a holistic understanding of how to architect seamless integration across heterogeneous systems. For CDSS literature survey studies, most studies were applied to specific CDSS types, either knowledge-based [12, 13] or non-knowledge-based [14, 15]; moreover, they focused on either EHR or CDSS integration, but no study focused on both EHR and CDSS integration.

This paper addresses these gaps by providing an architectural integration framework that unifies existing approaches, highlights emerging opportunities, and offers a foundation for future research in interoperable healthcare ecosystems. This comprehensive review of interoperability in EHR and CDSS systems, with the following contributions:

1. **Conceptual foundation** – Provide a clear overview of EHR and CDSS interoperability concepts and highlight their importance for holistic HIS integration.
2. **Integration techniques** – Review interoperability approaches, including standards, semantic web (SW) technologies, and artificial intelligence methods, for integrating heterogeneous healthcare data.
3. **Global perspective** – Emphasize the urgent need for **national and cross-border EHR integration** to strengthen healthcare systems.
4. **Novel classification** – Propose a three-level interoperability taxonomy:

- **EHR–EHR interoperability**: integration within or across heterogeneous EHRs.
- **CDSS–EHR interoperability**: integration between EHR data and CDSS knowledge/rules.
- **CDSS–CDSS interoperability**: knowledge integration across multiple CDSS platforms.

This classification provides a broader architectural perspective on interoperability and highlights future research pathways that have not been comprehensively addressed in previous surveys.

5. **Literature synthesis and future outlook** – Analyze recent research on EHR and CDSS interoperability, highlight current limitations, and identify future research directions.

The structure of the presented paper is described in Fig. 2. The remainder of this paper is arranged as follows. Section 2 reviews survey papers about interoperability in EHRs and in CDSSs. Section 3 describes the methodology used to collect and analyze the literature on EHR–CDSS interoperability and discusses the importance of interoperability for healthcare data integration. Section 4 introduces the background of EHRs and CDSSs, along with related concepts. Section 5 examines interoperability within EHR systems. While Sect. 6 focuses on interoperability between EHRs and CDSSs. Finally, the conclusion and main limitations are presented in Sect. 7.

2 Related work

In this section, recently published survey papers that are concerned with EHRs or CDSS domains were reviewed and discussed. According to this comparative review, the main limitations of these surveys were discussed to highlight the literature gap that our study focuses on.

2.1 Surveys of EHR interoperability

Miandoab et al. [16] investigated the interoperability requirements for heterogeneous HISs. Rao, and Manvi [8] explored the uses of Blockchain and AI technology in healthcare. The author's goal was to examine the benefits, problems, and difficulties of combining the two primary technologies, as well as potential future study areas in

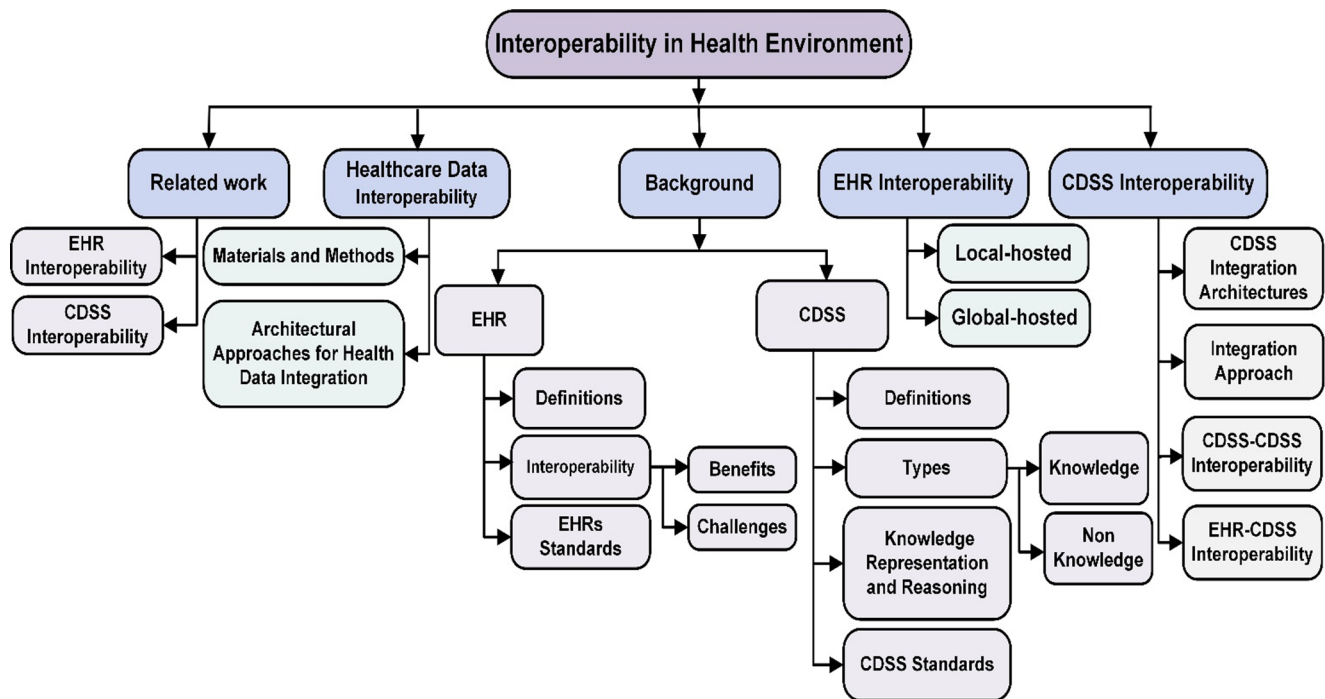


Fig. 2 The paper's structure

the field of healthcare. De Mello et al. [7] reviewed semantic interoperability (SI) in EHRs in great detail. The authors presented the most popular techniques, technologies, and situations for resolving interoperability issues, as well as a recommended taxonomy for SI in EHRs. Huang et al. [9] described different data fusion techniques that could be applied to combine medical imaging with EHR. Negro-Calduch et al. [17] tried to assess technological progress in EHRs. SONKAMBLE et al. [18] gave a thorough analysis of huge data stores for EHR modeling, open standards for EHR interpretation, and healthcare ontologies for knowledge representation in EHRs. Kline et al. [19] conducted a review to summarize the current studies in the field of biomedical machine learning (ML) by fusing dissimilar data. According to the authors, cancer and neurology were the two medical specialties that used multi-modal approaches the most frequently. The most popular method of data merging was early fusion. Peng et al. [20] investigated the state-of-the-art in health data integration as well as the applications of the integrated data. Zhang et al. [21] identified the primary obstacles and gaps in integrating health data from various domains and levels, and summarized the state-of-the-art methods for integrating EHRs and information. Fennelly et al. [22] highlighted research that gathered the essential organizational, technological, and human components for the deployment of an EHR to various stakeholders in various situations. Shafqat et al. [23] discussed the numerous appropriate healthcare data analytics methods, tools, and approaches that might be used in wireless, Internet of Things, and cloud settings and provided a thorough survey of various big data analytics integrated healthcare systems. Hammad et al. [10] examined the state-of-the-art in terms of SW for the healthcare sector. The authors talked about how various standards, methods, and viewpoints developed by the SW community could help in addressing the difficulties presented by big data in healthcare. DHAYNE et al. [24] aimed at studying data integration technologies, applications, and tools in healthcare. Kruse et al. [11] identified the barriers to using EHRs. The public-industry health could work with interoperability programs to fully adopt and make the EHR interoperable. Table 1 lists the suggested evaluation measures. Those measures were based on our study of the current literature. Table 2 analyzes the related work based on the suggested evaluation measures.

Table 1 EHR interoperability survey papers' assessment criteria

Question	Issue/ question
Q1	How many references did this survey review?
Q2	What was the period this survey adopted?
Q3	Did the survey present the research purpose?
Q4	Did this survey concern EHR standards for achieving interoperability? What are those standards adopted in the study?
Q5	Did this survey concern terminology? What terminologies or health repositories are used?
Q6	Did this survey concern SW technologies on achieving interoperability?
Q7	Did this survey handle uncertainty in the medical domain?
Q8	Did this survey improve the results using novel approaches and algorithms? What are the approaches used?
Q9	Did this survey explore the integrated data for correct decision support systems?
Q10	Did this survey mention future work or even adopt a new method for the EHRs data integration?

Table 2 Comparison of recent surveys in EHRs

Ref., Year	Design	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
[16], 2023	Systematic review	42	2003–2023	✓	✓	✓	✓	✗	✗	✗	✗
[8], 2023	Systematic review	61	2016–2022	✓	✗	✗	✗	✗	✓	✗	✓
[7], 2022	Systematic review	52	2010–2020	✗	✓	✓	✓	✗	✗	✗	✗
[9], 2022	Systematic review	54	2012–2020	✓	✗	✗	✗	✗	✓	✗	✓
[17], 2021	Systematic review	47	2010–2020	✓	✓	✗	✗	✗	✓	✗	✗
[18], 2021	Systematic review	158	2007–2021	✓	✓	✓	✓	✗	✓	✗	✓
[19], 2021	scoping review	202	2011–2021	✗	✗	✗	✗	✗	✓	✓	✗
[20], 2020	Literature review	73	2008–2018	✗	✗	✓	✓	✗	✓	✗	✗
[21], 2022	Scoping review	121	2009–2021	✓	✓	✗	✓	✗	✗	✗	✗
[22], 2020	Umbrella review	77	2010–2020	✗	✓	✗	✗	✗	✓	✗	✗
[23], 2020	A review	66	-	✓	✗	✗	✗	✗	✓	✓	✓
[10], 2020	A Survey	96	-	✓	✗	✗	✓	✓	✗	✗	✗
[24], 2019	Comprehensive Survey	189	-	✓	✓	✓	✓	✓	✓	✗	✓
[11], 2018	Systematic review	72	2012–2017	✓	✗	✗	✗	✗	✗	✗	✗

The authors in [16] tried to integrate interoperability principles into the healthcare sector and to achieve more efficient ICT (Information and communications technology) integration. So, the findings of this study could be distilled into the following statements:

1. DICOM and HL7 FHIR are the most frequently used EHR standards.
2. HIPAA and ASTM are the most frequently used security standards.
3. The most cited terminologies are ICD 10, SNOMED-CT, and LOINC.

The study [8] presented a combination based on AI “Artificial Intelligence” and Blockchain exhaustively. They could be influenced by the application of Deep Learning (DL) methods and Natural Language Processing (NLP) for more accuracy in interpretation. The integration of AI and agent-based systems into EHR enables the process of coordinating, decision-making, and taking suitable actions. The authors in [7] highlighted the role of EHR standards in achieving interoperability. OpenEHR, HL7, and ISO13606 were the three main standards mapped. Also, the authors ensured the importance of international terminologies for achieving global unified terms. SNOMED-CT, the most popular and semantically rich terminology, was highlighted by the authors [25]. Another terminology, ICD defines a range of illnesses, injuries, syndromes, and connected medical issues [26]. Also, this study showed a trend by integrating SW technologies and standards in achieving SI. The authors in [9] presented a global analysis of DL models that influence multiple modalities for medical imaging tasks.

The study in [17] concluded that when managing huge data, ML techniques perform better and take up less time. The study in [19] recommended multi-modal data integration to improve performance and make clinical

Table 3 CDSS survey papers' assessment criteria

Question	Issue/ question
Q1	Did this survey concern specific CDSS types?
Q2	Did this survey concern CDSS standards?
Q3	Did this survey concern interoperability in CDSS?
Q4	Did this survey concern ontology on CDSS rules management?
Q5	Did this survey explore CDSS integration with EHRs and integration architectures?
Q6	Q6: What was the period this survey adopted?

Table 4 Comparison of recent surveys in CDSS

Ref., Year	CDSS Type	Standards	Interoperability	Ontology	EHR Integration	CDSS Integration	Period
[14], 2020	NCDSS	✗	✗	✗	✗	✗	to 2019
[15], 2018	NCDSS	✗	✗	✗	✗	✗	to 2015
[13], 2022	RBCDSS	✓	✓	✓	✓	✗	2007–2019
[27], 2022	OBCDSS	✓	✓	✓	✗	✓	to 2022
[28], 2022	KBCDSS+NCDSS	✓	✗	✗	✓	✗	2000–2020
[29], 2019	-	✗	✗	✗	✓	✗	to 2018
[30], 2017	-	✗	✗	✗	✗	✗	2015–2016
[12], 2016	KBCDSS	✗	✗	✗	✗	✗	to 2015

NCDSS: Nonknowledge CDSS, RBCDSS: Rule-based CDSS, OBCDSS: Ontology-based CDSS, KBCDSS: Knowledge-based CDSS

decisions. The authors in [20] concluded that the integration of SW technologies and web application programming can cope with the EHRs interoperability challenges. The authors in [21] determined that data warehouses and federated systems were common and effective solutions in actual data integration systems. The authors in [22] found that usability, flexibility, interoperability, regulation, infrastructure, standards, and policies were all important for the success of the EHR. The authors in [23] developed a cloud-based smart-health platform united with IoT, embedding healthcare analytics for patients' diagnoses. The authors in [10] reviewed the semantic technologies' roles in transforming and extracting health data. Also, they reviewed the different methods to integrate heterogeneous health data. The study in [24] found that combining the recent models of DL, speech recognition, artificial neural networks, computer vision, and NLP could address the challenges of integrating unstructured and structured data.

This review presents a detailed survey of interoperability in distributed EHRs environments. It manipulates the integration of many different aspects, such as SW technologies, open EHR standards, global EHRs, and new approaches. It did not adopt a certain technology in interoperability. It introduces a fair discussion. In the following, we manipulate some limitations of the literature surveys.

1. Some surveys were concerned only with new approaches and neglected the role of standards and terminologies in integration [8, 9, 17, 24].
2. Many surveys ignored the uncertainty problem [8, 9, 11, 17, 19, 21–23].
3. Other surveys were concerned only with standards, terminologies, and SW technology and did not discover the role of new approaches [8, 10, 11, 16, 21].

2.2 Surveys of CDSS interoperability

For survey papers that are concerned with reviewing CDSSs, a list of suggested research questions to evaluate those papers is proposed in Table 3. These measures were based on our study of current literature. Table 4 analyzes the related work based on the suggested research question.

Earlier systematic reviews have addressed the use of a CDSS to evaluate its use and effectiveness [12, 27, 28]. These review papers were directed to a specific healthcare purpose or workflow. A systematic review [29], which focuses on the most common CDSS trends and characteristics, including system type, representation, integration,

knowledge formulation, and their technological features, was introduced. This review paper also developed a maturity stage model for CDSS from a decision-making perspective and discusses the maturity level of currently identified CDSS characteristics. Another recent systematic review that represents modern ontology-based CDSS rules [30] was introduced. This review elaborates that though ontology is utilized to supply CDSS rules, terminologies, and medical knowledge to a CDSS, it has not been utilized in CDSS rule management. Another paper performs a comprehensive literature review on the methods used for developing rule-based CDSSs with an emphasis on publications that offer a clinical assessment of the CDSS [13]. Several research questions were formulated to capture an understanding of diverse technical aspects of rule-based CDSSs, such as knowledge representation techniques containing clinical ontologies, EHRs interoperability, CDSS architecture, and standards. These review papers are within the scope of knowledge-based CDSSs. For non-knowledge CDSS, a review paper about non-knowledge CDSSs for diagnosing heart diseases in clinical settings is introduced [15]. Another machine learning-based CDSS survey can be found in [14].

3 Materials and methods

We outline the survey’s methodology in this section. Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) was what we adhered to [31] for searching and reporting the related studies published between 2017 and March 2023.

We look at the search terms, the data sources, the inclusion/exclusion standards, and the article selection standard as follows .

3.1 Search strategy

Several database engines were used to obtain related studies for this study, as displayed in Table 5. The study was limited to highly regarded journal papers. We also added Google Scholar to cover the literature on these bases.

3.2 Search queries

First, in the search process, we used a few keywords related to healthcare interoperability. Candidate phrases are originally established based on a preliminary search to discover similar studies. To avoid potential bias when looking for state-of-the-art studies, the following search terms and MeSH terms, which include generalized keywords, were used:

- (“Electronic health record” OR EHR) AND (“interoperability” OR “data integration” OR “semantic interoperability”).
- (“Clinical decision support system” OR CDSS) AND (“interoperability” OR “integration” OR “knowledge sharing”).
- (“EHR-CDSS integration” OR “CDSS-EHR interoperability” OR “health data exchange”)
- (“Healthcare standards” OR “HL7 FHIR” OR “openEHR”) AND (“interoperability framework”).

Table 5 Database engine

No.	Database engine	Link (Last Accessed on 1 March 2023)
1	IEEE Explore Library	https://ieeexplore.ieee.org/
2	PubMed Central	https://pubmed.ncbi.nlm.nih.gov/
3	Nature	https://www.nature.com/
4	ScienceDirect	https://www.sciencedirect.com/
5	Springer	https://link.springer.com/
6	ACM Digital Library	https://dl.acm.org/

Boolean operators (AND, OR) were used to combine terms, and searches were adapted for each database's syntax.

3.3 Article inclusion and exclusion criteria

To distinguish the most related publications, the exclusion/inclusion criteria were used depending on the study objective. We considered only the studies with matched inclusion criteria, while those that did not match the criteria were discarded. The exclusion and inclusion criteria are depicted in Table 6.

3.4 Study selection process

The selection process followed three phases:

1. **Initial screening:** Titles and abstracts were reviewed against the inclusion criteria.
2. **Full-text review:** Potentially relevant papers were read in full.
3. **Final inclusion:** Papers meeting all criteria were included for analysis.

3.5 Data extraction and synthesis

ns.

3.6 Choice of articles

The initial search in the databases produced $n=4495$ records that met the predetermined criteria. Reference list searches turn up an additional $n=175$ publications. After deleting 485 papers that were published in languages other than English and duplicates, we are left with 4185 candidate papers that meet our criteria for title, abstract, and keywords. After looking through the titles, abstracts, and keywords of $n=2710$ papers, $n=1160$ eligible papers remained, 224 for EHR interoperability, and 148 for CDSS interoperability. The application of the PRISMA methodology in our study is depicted in Fig. 3.

3.7 Architectural approaches for interoperability

Interoperability aims to share data among all HIS participants, such as clinicians, nurses, and labs, in a meaningful, smooth, and seamless way. It is considered a prerequisite for accurate systems integration. Respectively, utilization and integration are the products of interoperability. Thus, supporting interoperable systems construction would allow data reuse and make clinical research inside healthcare institutions a reality. Learning healthcare system cycle (LHSC), a direction that uses big data in the healthcare domain, has been recently reinterpreted

Table 6 Inclusion and exclusion Criteria

Inclusion criteria	Exclusion criteria
Published in a journal with peer review	Duplicate articles
Written in English	Not related to the healthcare domain
Published between September 2017 to March 2023	Not concerned about health data integration
Manipulating approaches to aggregate different health data	Review articles
Directly related to interoperability or semantic interoperability in EHRs and CDSSs.	Studies did not use the theory of IT.
Focused on healthcare environments, clinical or medical data, or EHRs data exchange.	
Proposing solutions that support health data integration.	

Fig. 3 The PRISMA flow diagram of the article's selection process

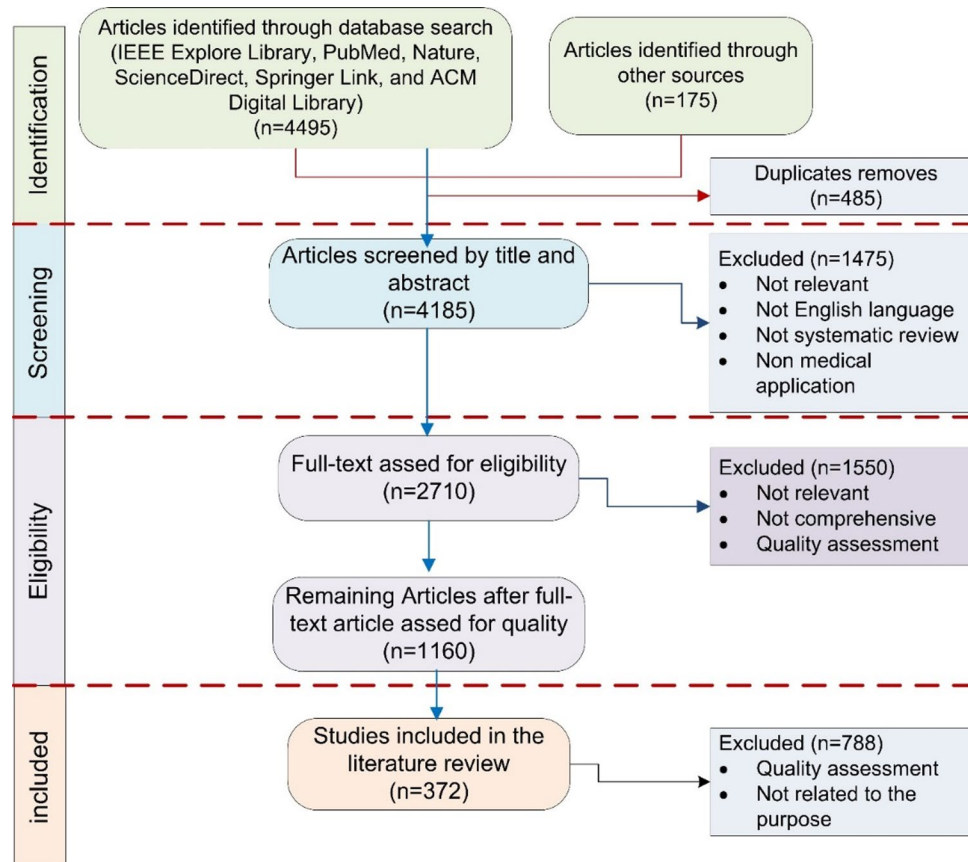
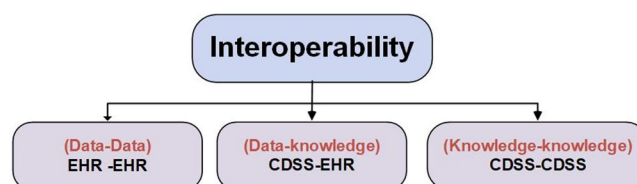


Fig. 4 Interoperability architectural dimensions



within the medical informatics sector [32, 33]. It is founded on two complementary activities, the first focuses on utilizing medically generated data for research purposes (care informs research), and the second focuses on including big data to guide clinical decision-making to develop new healthcare systems (research informs care). Thus, in this direction, healthcare research and practice have to work together in a unique way to support workflow integration.

Integration between EHRs and CDSSs to support decision-making or clinical practices is a major step toward realizing a full LHSC. We introduce a new architecture-based interoperability classification represented in Fig. 4 for achieving comprehensive interoperability in healthcare environments. In this classification, interoperability is organized into three types according to various integration architectures between various HISs. These types are:

First, EHR-EHR interoperability, which is concerned with local or global EHR data integration within single EHRs or between various EHRs.

Second, CDSS-EHR interoperability is concerned with the integration between EHRs data and CDSS knowledge.

Third, CDSS-CDSS interoperability is concerned with knowledge integration between various CDSSs.

These dimensions provide a foundation for comprehensive health data integration, supporting the development of a full LHSC system. Based on these categories, Fig. 5 proposes a reference architecture of a full LHSC ecosystem for integration of various EHRs and CDSSs or between each other.

From a data interoperability perspective, it shows how various EHRs systems are integrated either through a single EHRs data warehouse or federated EHRs systems. From a knowledge interoperability perspective, various CDSS types (knowledge or non-knowledge) with different architectures interact with each other. This integration could be through a single CDSS data warehouse or federated CDSS systems. In this interoperability dimension, knowledge-based CDSS, which may utilize ontology, and non-knowledge-based CDSS, which is based on ML could be combined into a hybrid CDSS. Finally, with data knowledge interoperability, the EHRs system is integrated with CDSSs to achieve the two complementary actions: data to knowledge and knowledge to practice.

This architecture facilitates integrating patient care data with research data, not only within a single hospital but also across several hospitals. According to the proposed full interoperability-based framework, a HIS could be more effective when it supports clinical workflow and data integration between various EHRs systems and CDSS systems by integrating CDSS into the care process.

On the other hand, this interoperability architecture is designed not only to ensure semantic and structural integration between heterogeneous EHR and CDSS systems but also to address critical performance evaluation metrics. By explicitly addressing these evaluation metrics, the proposed framework demonstrates its potential to

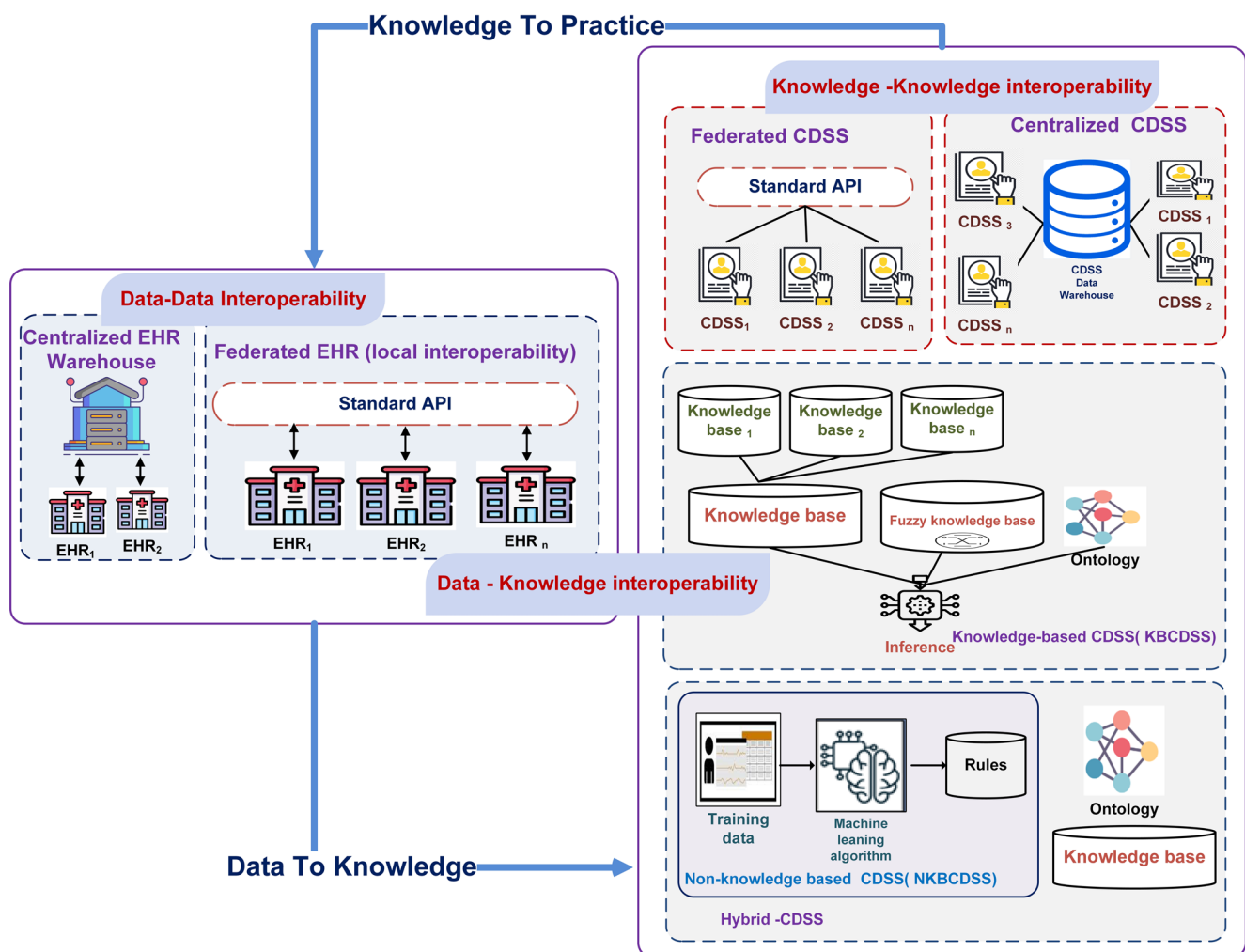


Fig. 5 The proposed conceptual model of the full LHSC ecosystem based on new interoperability dimensions

deliver low-latency, highly scalable, and high-throughput interoperability, thereby strengthening the operational reliability of future patient-centered healthcare ecosystems.

Layered architecture systematically organizes data sources, interoperability mechanisms, decision-support modules, and end-user applications, as represented in Fig. 6. At the **data layer**, distributed EHR databases, patient-generated data, and external sources (labs, imaging, wearables) are unified to minimize latency in data retrieval while supporting high-throughput ingestion of streaming inputs. The **integration layer** leverages interoperability standards (HL7 FHIR, openEHR, DICOM), secure APIs, middleware, and harmonization services to ensure seamless, real-time communication, reduce semantic ambiguity, and scale across institutions without loss of usability. At the **CDSS layer**, knowledge-based, AI/ML-driven, and hybrid systems combine symbolic reasoning with predictive analytics to deliver robust, explainable, and scalable decision support, optimizing response time and clinical usability. Finally, the **application layer** incorporates clinician dashboards, patient portals, and mobile/web applications that provide context-aware, real-time recommendations, reducing perceived latency, improving user adoption, and enabling concurrent multi-user access.

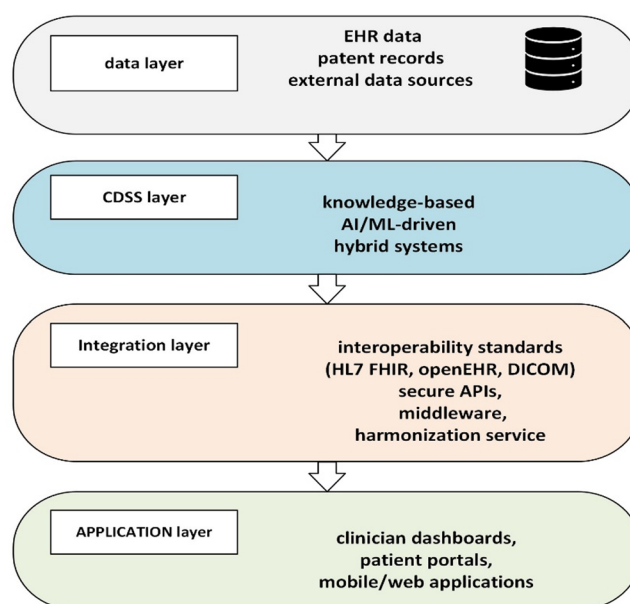
Collectively, this architecture not only supports **EHR–EHR, CDSS–EHR, and CDSS–CDSS interoperability**, but also embeds evaluation considerations—latency, scalability, throughput, and usability—into its design, thereby offering a resilient and AI-ready healthcare ecosystem capable of unifying data and knowledge for patient-centered care.

4 Background

4.1 Electronic health record

With the increasing growth of medical science, more information is needed for specialists in treating patients. Patient data involves various types of data that could be stored or linked in an EHR system. It associates all patient data from diversified systems. Various definitions of EHR appear in the literature [34–37]. The most recent definition of EHR in 2019 was “a safe, timely, patient-focused information source for medical professionals. By giving physicians access to patient health record information when they need it and combining evidence-based decision support, the EHR supports their decision-making. The EHR automates and streamlines the workflow of

Fig. 6 Layered Architecture for EHR and CDSS Interoperability



the clinician, ensuring that all clinical information is delivered and reducing response times that cause gaps or delays in care [37].

All the definitions of EHR are effectively alike but change in emphasis, such as information source, value for healthcare, clinical representation, medical functions, or involved stakeholders [34, 38]. EHR definitions in [38, 39] are concerned only with storing EHRs in an electronic device “media”. US National definition [8] related EHRs with interoperability with standards; however, definitions [34, 36, 37] are concerned with a more comprehensive view of EHRs as reusing and linking electronic records with each other. In some contexts, EHR has even been used to describe more widely interventions such as CDSSs [37].

EHRs store the patients’ information in many different formats. These formats of information greatly affect the ease of access and quality of the data. Data from EHRs may be unstructured, semi-structured, or Structured. Structured EHRs data is stored in database tables with a fixed schema. The most used information, such as demographic information (e.g., birth date, name, race), vital signs (pulse, blood pressure, height, weight), encounters (e.g., discharge and admission data), diagnosis codes (current and historic), laboratory results, procedure codes, medications, allergies, social information, and some are all stored in structured tables. Semi-structured EHRs data (XML files, HTML code, e-mails) is between structured tables and unstructured free text. Unstructured EHRs data (images, e-mails, video, and reports) are mostly stored in free text, such as clinical notes and familial history of diseases. One of the main challenges of interoperability in distributed EHRs is that most EHR data is unstructured [40, 41], requiring specialized extraction tools necessary to deduce meaningful information. In the following section, we provide a brief introduction to interoperability in the EHRs environment, its levels, its benefits, and its main challenges.

4.1.1 EHR interoperability

The ability of different applications to exchange, access, integrate, and use data in a coordinated manner through the use of standards and shared application interfaces within and across organizational, regional, and national boundaries could be characterized as interoperability in the healthcare domain. This would enable timely and seamless portability of information and improve health outcomes [42]. There are several interoperability definitions in the literature [43–46]. However, the HIMSS definition is the most comprehensive as it uses the term ‘interoperability’ to refer to a wide range of EHRs, from in-house technologies to national infrastructure [47]. According to HIMSS, interoperability has four levels: foundational, structural, organizational, and semantic [4, 47].

The interconnectivity requirements necessary for one system to communicate with and receive data from another are established by foundational interoperability [47]. The syntax, format, and organization of data sharing, even at the data field level for interpretation, are all defined by structure. It is characterized as the capacity of two or more systems to exchange data using particular communication protocols and data formats [47]. To make data sharing and use within entities, organizations, and people easier, organizational considerations include policy, governance, legal, and organizational factors. Shared trust, consent, and integrated end-user workflows are made possible by these elements. Semantic interoperability is the capacity for systems to understand shared data at the level of fully defined domain ideas [48]. It tries to ensure that systems or organizations comprehend and analyze data regardless of who is engaged and to share data among systems or organizations [15]. For real machine-to-machine interoperability of EHR systems, the system must fulfill all the interoperability levels [49]. Figure 7 gives the reader an overview of interoperability in EHRs: levels, standards, terminologies, and approaches.

a. EHRs interoperability benefits

EHRs have significantly impacted healthcare, offering many advantages such as enhanced collaboration, increased efficiency, patient-centered care, increased patient engagement, reduced errors, and improved care quality [50, 51]. By sharing data across different organizations, doctors can get better insight into patients’ medical histories

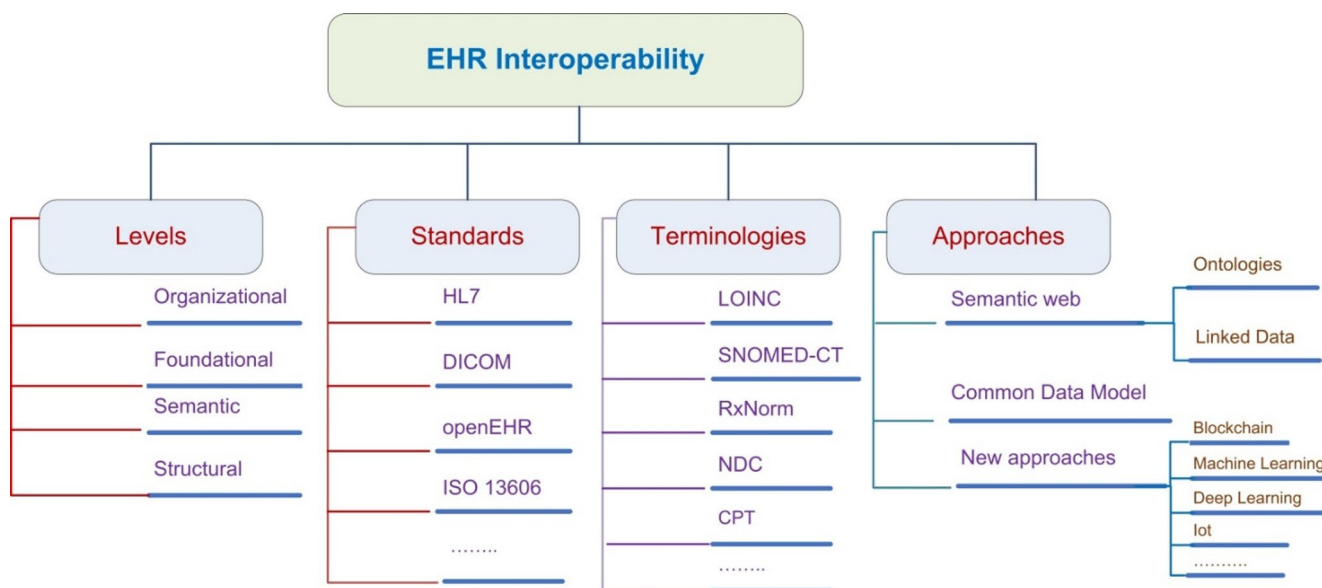
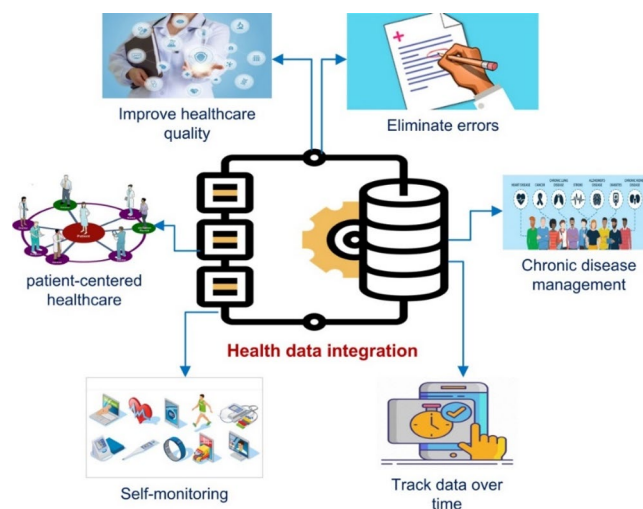


Fig. 7 EHRs interoperability: levels, standards, terminologies, and approaches

Fig. 8 EHRs interoperability benefits



and make rich, informed decisions about their treatment plans [52]. An interoperable environment improves healthcare delivery by making the right data available to the right people at the right time. It enables physicians to track data over time and aids in monitoring and enhancing the general quality of care provided within the practice [53]. In addition, it exchanges data between physicians and patients. Patients anticipate doctors having access to their full medical records. When physicians have access to this data, they can make the best possible medical decisions and prevent duplicating procedures and tests [17]. Some interoperability benefits in the healthcare domain are shown in Fig. 8.

b. EHRs interoperability challenges

Although EHRs interoperability has many benefits and importance, it has many issues associated with its implementation, such as:

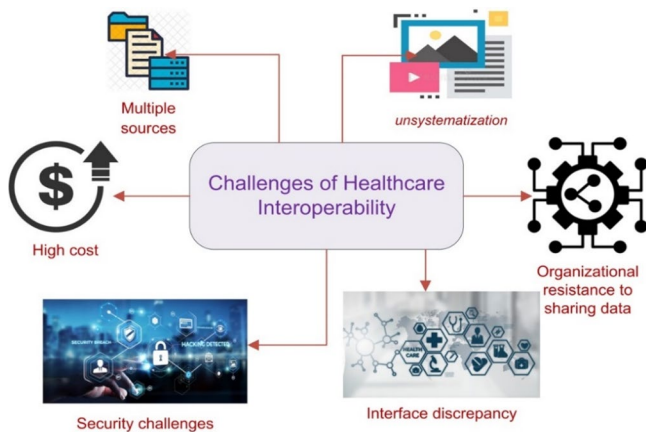


Fig. 9 EHRs interoperability challenges

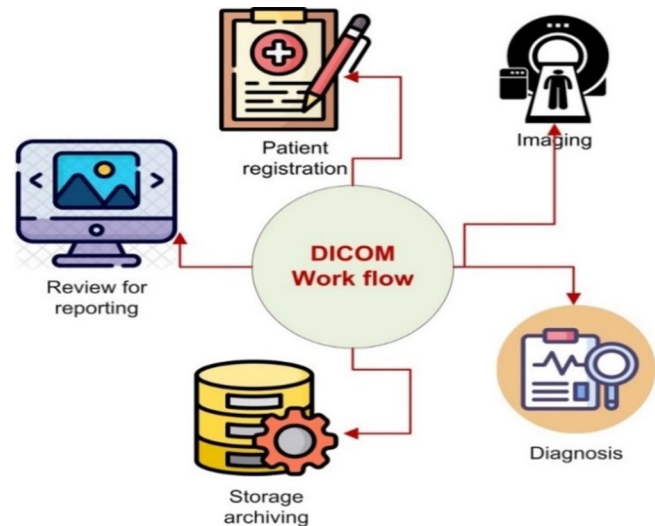


Fig. 10 DICOM imaging standard workflow

1. Systematization of data: One of the more complex challenges of EHR interoperability is inconsistent data management. Data could be stored in different databases and have a variety of data formats that are not easily compatible with one another [49].
2. Data confidentiality and privacy: EHR is endangered by threats from various stakeholders. One of the biggest obstacles facing EHR interoperability is cultural, not technological, because interoperability in healthcare requires close collaboration and coordination among diverse stakeholders [54]. Some interoperability challenges in the healthcare domain are shown in Fig. 9.

4.1.2 EHRs interoperability standards

To solve the interoperability issue with EHRs, many EHRs standards were proposed, such as the Health Level 7 (HL7) FHIR [55], openEHR [56], and ISO/CEN 13,606 [57]. These guidelines seek to format and mark up the clinical material when exchanging.

- OpenEHR is a multi-level modeling strategy that uses templates, archetypes, and a reference model (RM). RM could be defined as a stable and formal model that defines health information logical structures for supporting syntactic interoperability [56]. The “ADL” or Archetype Definition Language is used to express OpenEHR archetypes.
- Fast Healthcare Interoperability Resource, commonly known as FHIR, is an HL7 specification for EHRs interoperability [58]. It represents and shares information among organizations and clinicians in a standard way, independent of the way they are represented or stored. It joins the previous standards’ best features of a common specification [59].
- Digital Imaging and Communications in Medicine (DICOM) is referred to as the de facto standard for medical image communication [60]. The handling, printing, storing, and transferring of data in medical imaging are all governed by this standard [60]. Its objective is to increase the effectiveness of workflow between imaging equipment and other healthcare information systems. Binary encoding is used by DICOM, and hierarchical lists are recognized by numerical tags. Figure 10 shows the main DICOM imaging standard workflow.
- Integrating the Healthcare Enterprise (IHE) encourages meeting specific clinical demands to enable the best possible patient care. Its principal objective is to promote the fusion of digital healthcare resources. IHE

systems let healthcare professionals use information more effectively and communicate with one another more effectively. Table 7 includes a comparison of some standards according to the following criteria: interoperability level, data models the standard supports, its main services, characteristics, and whether it supports CDSS or not.

4.1.3 EHRs interoperability open-source tools

The most popular method for achieving interoperability relies on using open application programming interfaces (APIs) [61]. APIs enable different sources of data to be shared between EHRs and health information technology systems. Open-source tools enable more efficient operations and encourage better outcomes across the healthcare ecosystem. EHR software systems include many EHR vendors, such as openEMR [62], Epic EHR [63], Practice Fusion EHR [64], GNU Health [65], OSHERA Vista [66], and OpenMRS [67]. We give the reader a quick overview of some of these systems in this section.

Mirth Connect is an open-source tool to transform CSV patient data files into FHIR resources [68]. It provides healthcare partners with the necessary patient data at critical times. It also overcomes hurdles in data exchange with scalable, secure, and cost-effective interoperability solutions [69].

OpenEMR: “Open Electronic Medical Record” is a more well-liked open-source EHR and practice management system for healthcare [62]. It is ONC Certified, a fully integrated EHRs, and has free support. Numerous platforms, including Linux, Windows, Mac OS X, and others, can execute it. OpenEMR can perform tasks such as searching for available appointment slots on the calendar, tracking patient demographics, and providing basic support for FHIR. There are OpenEMR implementations in the UK, South Korea, India, Brazil, and the United States [70].

Epic EHR: It is a cloud-based EHR solution introduced to several specialties [63].

Practice Fusion EHR: Practice Fusion is a cloud-based EHRs provider that creates integrative environments for care professionals and treatment teams [64].

GNU Health: it is a released hospital information system (HIS) with a strong reliance on social medicine and public health. Its main functions involve laboratory information system management [65].

4.2 Clinical decision support systems

A CDSS is a clinical system that utilizes medical knowledge within healthcare data to present personalized advice for patient care [71]. It could be defined as “an active intelligent system able to assist medical professionals by generating recommendations and decisions depending on patient healthcare information and related medical facts

Table 7 EHRs standards comparison

Standard	Interoperability level	Support archetypes	Data models supported	Characteristics	Services	Support CDSS
OpenEHR	Syntactic, Semantic	✓	Structured, Semi-structured	Widely used Service-oriented interface Open software	Patient-centered	✓
HL7-FHIR	Syntactic, Semantic	✓	Structured, Semi-structured	Widely used Flexible	Store, retrieve, update, and share	✓
DICOM	Syntactic	✓	Structured, Semi-structured, Unstructured	Widely used Diverse medical system interconnectivity Complex and large Less storage space	Store, query, and retrieve	✗
IHE	Syntactic	✗	Semi-structured	Easier to implement, Seamless, and secure access to data	Query, and retrieve	✗

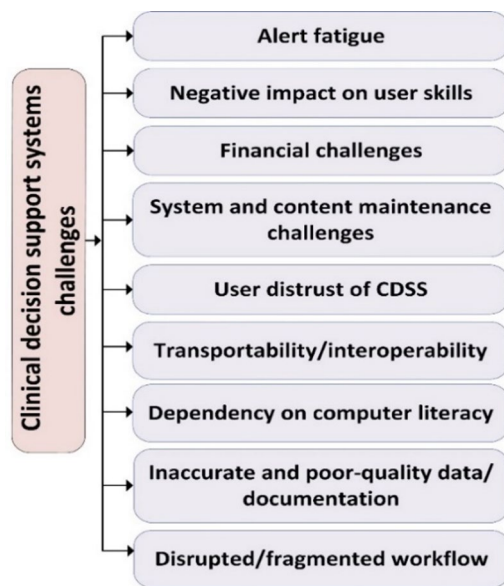


Fig. 11 Clinical decision support systems challenges

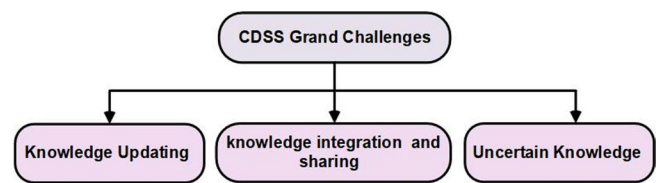


Fig. 12 A CDSS's main challenge

analysis" [72]. A CDSS could provide staff, clinicians, patients, or other individuals with patient-specific data and knowledge at the right times to improve healthcare [73, 74].

From the perspective of system architecture, a CDSS, which is used as a tool for diagnosis, is an expert system designed to provide the clinician or physician with useful information and recommendations at the point of care. The main functions of a CDSS are supporting decision-making, enhancing the quality of patient care, reducing errors and costs, boosting productivity, and improving diagnostic and predictive capabilities of patients to the best available level [13].

ACDSSs encompass various tools for improving decision-making in the medical workflow. These tools involve computerized alerts, clinical guidelines, condition-specific order sets, focused patient data reports, and diagnostic assistance [75]. The extent of the functions provided includes alarm systems, diagnostics, drug control, disease management, and much more. These days, CDSSs can offer several functionalities such as secondary diagnostic and administrative functions, disease treatment monitoring, prescriptions, and medication control. There are various challenges associated with these systems' functionalities [73, 75–78], which are represented in Fig. 11.

These challenges could be summarized into three main grand challenges in Fig. 12. These challenges are: first, integrating CDSS with the EHR and sharing CDS knowledge, modules, and services. Second, handling uncertain knowledge, and third, updating the knowledge.

4.2.1 CDSS types

CDSSs can be classified in several ways, but the most applicable one is the classification of CDSSs: knowledge-based CDSSs and non-knowledge-based CDSSs. In other words, there are two main categories of CDSSs according to how they obtain and infer medical knowledge and make decisions [13, 75, 79]. Knowledge-based systems are based on a wide clinical knowledge repository with subject-specific knowledge extracted from the graphical representations that represent the relationship between symptoms and disease with conditional probabilities. Non-Knowledge-based ML CDSS, also known as a data-driven system, learns or trains on large datasets of clinical data from historical experiences to get patterns without needing to write rules or provide expert input. They are described as non-knowledge systems because they do not have any knowledge before an ML algorithm procedure takes place [75]. Artificial Neural Networks (ANN) are the most popular type of non-knowledge-based

Table 8 Differences between Knowledge- and non-Knowledge-based CDSSs

	Advantageous	Dis-advantageous	Techniques
Knowledge-based systems	The high degree of flexibility and agility for constantly changing clinical knowledge that is with new circumstances and discoveries.	Needs a huge number of rules to acquire experts' knowledge in complex clinical decisions. Lack of clinical work system integration Knowledge bases must be regularly updated as new information becomes available. The difficulty in implementing knowledge bases that emphasize disease and treatment probabilities is that many of these probabilities are unknown in the clinical setting.	Bayesian networks Probabilistic reasoning Graphical representations that catch the symptoms and disease relationship.
Non-Knowledge-Based systems	Solve complex decision-making problems. Knowledge acquisition process requires a long time and extensive human effort. Automatic rule generation by analyzing the massive amount of evidence-based research. No need for prior knowledge Can process incomplete data	Demand a huge amount of labeled data for training algorithms. Data availability problems. Do not offer the reason for the made decisions (black boxes). The training process is very time-consuming	Artificial neural networks Natural language processing Support vector machines Data mining Genetic algorithms Natural language processing

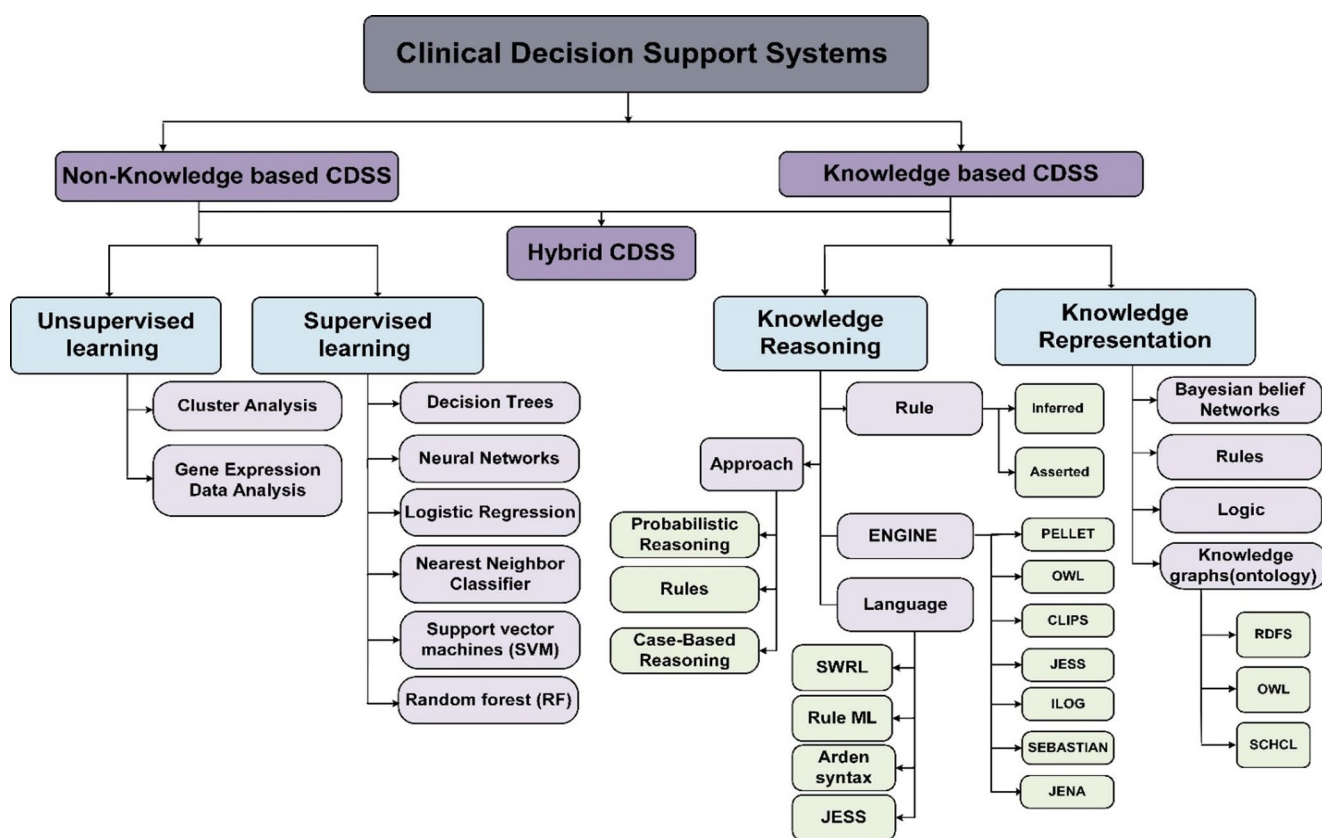


Fig. 13 CDSS types and main technologies

CDSSs [7]. Table 8 displays the main advantages, disadvantages, and techniques of knowledge and non-knowledge-based systems.

CDSS is based on various standards, technologies, and approaches used to develop it. As a result, it may be challenging for medical practitioners to choose the best solution in each situation. The main goal of Fig. 13 is to represent different CDSS types and different technologies related to them to support a better understanding of the diverse technical characteristics of a CDSS and offer guidance on the most appropriate solutions.

Knowledge-based systems perform various functions such as knowledge acquisition, knowledge translation, and logic-based reasoning, and use data from various sources, such as approved clinical practice guidelines (CPG), evidence-based medical literature, and patients' EHR [80]. As represented knowledge reasoning is based on some criteria, such as the reasoning approach, the type of inference engine used to generate rules, how rules are generated, whether they are asserted rules or inferred, and the language that is used to represent rules. For non-knowledge-based systems, these systems are based on ML, which are usually divided into supervised learning and unsupervised learning. Finally, there is a third CDSS type, which is a hybrid CDSS that combines both non-knowledge-based CDSS and knowledge-based CDSS.

4.2.2 Knowledge representation and reasoning

Contemporary CDSS is rooted in early expert systems. Knowledge-based CDSS rose out of the native realization that medicine was a good field for utilizing such knowledge [76]. It is comprised of three main architectural components: the medical knowledge base, the inference mechanism (reasoning), and the EHRs, even though the EHRs may be a separate system. A particularly important feature of the inference engine is its mutual exclusion from the knowledge base.

Knowledge representation is employed to provide a CDSS with information that improves the meaning behind these facts to be clear to users. The knowledge representation scheme combines fundamental domain-related facts to create the core knowledge base. The effectiveness of a knowledge representation schema significantly influences the types of problems that are addressed as well as the approach used to solve them [76]. Medical knowledge is typically categorized into two classes: procedural and declarative. While procedural knowledge provides a more linear description of what actions or conclusions are possible with the knowledge, declarative knowledge consists of simple statements and propositions presenting facts [81]. There are a variety of approaches for representing clinical knowledge in CDSS systems. Each method has significant strengths and weaknesses [82]. Table 9 represents the main declarative representation approaches of knowledge-based CDSSs.

As the CDSS domain of knowledge broadened, many promising methods to enable inferential reasoning within CDSSs emerged. There are several types of reasoning in CDSSs. The main advantages and disadvantages of these types are represented in Table 10 [76].

Table 9 Knowledge-based CDSS representation techniques

Approach	Approach	Advantageous	Disadvantageous
Logic(declarative)	Represented in terms of propositions to form sentences. Declarations are considered to be either true or false	First Order Logic (predicate) allows splitting statements and creating new declarations	Propositional logic is not flexible
Rule-Based Approaches (procedural)	Store knowledge utilizing IF-THEN rules and forward chaining till a decision has been reached.	Offer inspectability and editability	Rules are individually triggered rather than chained together.
Bayesian Belief Networks	Store numeric, probabilistic relationships between entities in the graph A tree of nodes and edges to link them.	Accurate in case the objective is to make a classification of some clinical phenomena. Flexibility Ability to capture difficulty-mapped knowledge	Limited capabilities for on-the-fly medical therapy. Not suitable for multiple symptoms
Knowledge graphs(ontology)	Store symbolic, logical connections amongst the entities, besides several properties of each entity.	Ability to make inferences about complex situations. Domain-independent knowledge representation Flexible in integrating, managing, expanding, and applying knowledge from diverse sources. Adapted to the needs of users and permits simpler knowledge sharing among domain applications. A shared, machine-explainable resource for evidence-adaptive CDSS	The recognition of entities requires previous knowledge of the domain. Creation and maintenance of knowledge graphs

Table 10 CDSS reasoning: Advantageous and disadvantageous

Approach	Advantageous	Disadvantageous
Rule-Based (logical) reasoning	Simplicity	Laziness, theoretical ignorance, and practical ignorance
Causal Reasoning	Ability to analyze disease interaction, describe disease progression, and understand specified disease mechanisms. Flexibility to determine situations where a hypothesis can explain only a part of a finding.	Lacking mechanical knowledge of many important diseases results in general disease-tracking being difficult to successfully implement. Ambiguity Temporal relationships between findings
Probabilistic Reasoning	The capability of recognizing the conditional distinctness of diverse findings	It needs careful development, a process that depends on several assumptions and large amounts of input data.
Case-Based Reasoning	Ability to solve open-ended problems quickly and non-algorithmically. Ability to work with complex cases.	The efficient indexing issue is a major concern in large knowledge bases.

4.2.3 CDSS standards

Standards are essential in systems development as they can shorten development times and improve reliability. Even with huge CDSS development efforts. It still suffers from interoperability problems. Many CDSSs are standalone systems or systems that cannot effectively interact with other systems [75]. Usually, standards initially aim to resolve interoperability at the syntactic level (i.e., data structure and format). Interoperability was addressed by standardizing various data to a common model, depending on the OpenEHR archetypes reference information model or the Health Level Seven (HL7) standard, which includes [13]:

- HL7 CDA (Clinical Document Architecture) [83] is an XML-based standard proposed to identify the encoding, semantics, and structure of clinical documents for healthcare data exchange.
- HL7 Arden Syntax [84] is used for the representation of clinical knowledge.
- HL7 vMR (Virtual Medical Record) [85] is used to represent the data in a CDSS engine. It could be regarded as an intermediary data model between database formats and standards-based CDSS.
- HL7 InfoButton [86] is a CDSS standard used to request context-specific clinical knowledge from online resources.

Because they developed independently, previous CDSS standards were always interoperable with each other [87]. New CDSS integration standards were introduced to support CDSSs sharing at several levels (logic, apps, or services). These standards are Fast Healthcare Interoperability Resources (FHIR), Clinical Quality Language (CQL), Substitutable Medical Applications and Reusable Technologies (SMART), and CDS Hooks.

- SMART [88] is developed to facilitate the EHR-agnostic medical applications integration within EHR systems utilizing present web standards.
- The FHIR [89] standard aims to simplify EHR-based data sharing. So, it has become extensively adopted for clinical data integration projects. This standard is proposed to tackle the technical and semantic complexity of healthcare data exchange.
- CQL [90] offers a standard methodology for representing “if-then” decision rules. It could be applied to determine the data model and the needed patient data.
- CDS Hooks [91] is a specification used to deploy and integrate CDSS within the EHR via web services, in which a Hook is an event that is automatically started according to particular user actions.

5 EHR interoperability

Interoperability in healthcare is an obligation; it supports the creation of collaborative solutions, integrated services, and interoperable systems. There are mainly two types of EHR interoperability according to where EHRs data are stored: Locally hosted EHRs and globally hosted EHRs.

5.1 Locally hosted EHRs

The primary purpose of a local-EHR system is not only the care of a patient within a single hospital or other healthcare organization, but also the support for shareable EHRs [92]. EHRs contain heterogeneous information that involves patient demographics, laboratory data, past medical reports, medications, radiology reports, and vaccinations. EHRs now store data generated by wearable technology and applications in addition to patient-provided data [4]. Several approaches have been proposed to achieve interoperability in heterogeneous EHRs. Here, we classified into three major groups: EHRs standards, SW technologies, and modern learning approaches.

a. *Standard-based Approach*

Due to the requirement for storing, sharing, exchanging, and querying data throughout different hospitals, medical information standards are receiving more and more attention. EHR standards allow various EHR systems to efficiently share data and communicate with one another. There are several standards for healthcare interoperability [55, 93, 94]. Many articles adopted EHRs standards to achieve interoperability, such as Sachdeva and Bhalla [95] discovered the knowledge representation role in achieving semantic exchange of health data. CEN\EN 13,606 and openEHR standards were used. SUJUDI and HERYAWAN [96] developed an automatic mapper from the openEMR system so that its data could comply with the FHIR standard; the attempt was made to apply interoperability of healthcare data. Lazarova et al. [97] aimed to create, build, and test new modular EHRs for use in select local hospitals' cardiological units. Federated SQL Server databases served as the foundation for the EHRs' architecture. Halford et al. [98] provided DICOM to accomplish the standardization of the neurophysiology format because the integration of neurophysiology data with existing DICOM-supported elements, such as ECG (Electrocardiography), video, and pictures, as well as the ease of integration with hospital long-term PACS storage systems, made these elements attractive. Saripall et al. [99] presented an HL7 FHIR-based framework to achieve both semantic and structural interoperability. This study leveraged RxNorm and SNOMED for the semantic standards and other supporting systems. It exposed health data as a service using RESTful and API protocols. Also, it investigated a working prototype of a mobile device that can communicate with both standards in both directions.

Kiourtis et al. [100] promised interoperability in healthcare via transforming health data to the HL7 FHIR structure. Rosa et al. [101] created a services platform that offered a repository of data for helping persons who were in line with the FHIR specifications. Maia et al. [102], in the Brazilian state of Minas Gerais, suggested that an archetype development approach be used to complement the EHR. Along with the standard governance procedures for SUS healthcare records, they incorporated Brazilian regulations regarding document storage [103]. Hong et al. [104] developed the NLP2FHIR framework for FHIR data normalization, which essentially included the following modules: (1) a core NLP engine module with an FHIR-based system; (2) a structured data integrating module; and (3) a normalization content module. Min et al. [105] recommended a strategy based on openEHR to improve the SI clinical data registry. Data registry collecting, data element definition, archetype modeling, template revision, and implementation were the five primary steps of the method. Table 11 analyzes the related studies that adopted standards for achieving EHRs interoperability based on the suggested evaluation measures shown in Table 12.

The authors in [95] presented diverse archetype representation technologies, such as XML to ADL to OWL, through the KnowledgeRep simulation model. The semantics of the archetypes were provided by terminology binding (SNOMED-CT). The archetype's nodes' meaning was given references to external terminology using

Table 11 Brief of articles that adopted standards for achieving interoperability in distributed EHRs

Study, Year	Adopted standard	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
[95], 2022	OpenEHR, CEN 13,606, and HL7 CDA	Structural, Semantic	✓	✗	✗	✓	✓	✗	✓
[96], 2022	HL7 FHIR, OpenEMR	Structural	✓	✓	✗	✗	✓	✗	✓
[97], 2022	HL7-(V2), FHIR	Structural	✓	✓	✗	✗	✓	✗	✓
[98], 2021	DICOM	Structural	✗	✗	✓	✗	✗	✗	✗
[99], 2019	HL7 FHIR, OpenEMR.	Structural, Semantic	✓	✓	✗	✓	✓	✗	✓
[100], 2019	HL7 FHIR	Structural, Semantic	✓	✓	✗	✗	✓	✗	✓
[101], 2019	HL7 FHIR	Structural	✗	✗	✗	✗	✗	✗	✓
[102], 2019	ISO/ CEN 13,606	Semantic	✗	✗	✗	✗	✗	✗	✗
[104], 2019	HL7 FHIR	Structural, Semantic	✓	✓	✓	✓	✗	✗	✓
[105], 2018	openEHR	Semantic	✓	✓	✗	✗	✗	✗	✓

Table 12 Locally hosted EHR interoperability papers' assessment criteria

Question	Issue/ question
Q1	What is the level of interoperability this study supports?
Q2	Did the EHR approach provide automated processing for structured content?
Q3	Did the used approach permit explicit record retrieval for a specific patient, relying on an incoming request?
Q4	Did it concentrate on the medical imaging sector/ unstructured data?
Q5	Was the proper terminology used?
Q6	Did the study use any of the other technologies besides the approach used?
Q7	Did this literature handle vague problems in the medical domain?
Q8	Did the study do any experiments and obtain results?

textual descriptions. The authors in [96] implemented and evaluated the Naïve-Bayesian, Decision Tree, and rule-based classifiers, resulting in 100% accuracy. Their results inferred that the rule-based technique made better results than Naïve-Bayes for development. The authors in [97] presented an architecture that integrated a frequently used cardiology EHR system with the regional health information infrastructure (RHII) system in the Liguria region of Italy; all RHII documents were given as HL7 CDA, and messages were sent using HL7 Version 2 (V2) and/or HL7 FHIR. The authors in [100] intended to create data for healthcare ontologies. Then, using their Levenshtein distance, the semantic and syntactic similarities of HL7 FHIR resources' ontologies were determined. The authors in [104] achieved an F-score performance ranging from 0.690 to 0.995 for several FHIR elements. The authors in [105] built a Coronary Computed Tomography Angiography (CCTA) registry as a case study. It has 183 data items, 20 of which are archetypes. There is a total of 45 semantic overlaps between CCTA and EHR data components. The 10 recycled EHR archetypes contain 38 (84%) of these CCTA data components.

After the discussion of some related literature based on using standards in achieving EHRs interoperability, the following points are discussed:

1. All literature was not able to handle vagueness and uncertainty in the medical domain.
2. Most of the literature focused only on using standards in structured data, whilst they were not able to deal with unstructured data.
3. EHRs standards can achieve only structural interoperability, not semantic interoperability. Studies in [95, 100] achieved SI that relied upon ontologies.
4. The extracted data shows the most choice of multilevel approaches, such as ISO/CEN 13,606, openEHR, and HL7 formats. Health systems are widely adopting the FHIR standard for exchanging information [96, 97, 99–101, 104].
5. There is no universally accepted EHR standard. The interchange and integration of data among systems with multiple standards is a significant problem that needs to be controlled because the EHR standards are managed by different nations and diverse companies [100].

6. In most literature, to achieve interoperability, EHR standards must rely on other technologies as ontologies [106].

b. *Semantic web-based approach*

SW was introduced to search, integrate, reuse, and share information [107]. To enable semantics encoding with the data, technologies such as Resource Description Framework (RDF) [108] and Web Ontology Language (OWL) [109] are used. It depends on how semantic metadata, which provides details about the content of the text, is used. It enables machines to comprehend the semantics of information in this way. For example, ontology can describe concepts, categories of things, and relationships between entities. These embedded semantics offer important advantages in operating with heterogeneous data sources and data reasoning. In this part, we manipulate some screened articles based on the SW adopted in solving EHRs interoperability problems. For example, Touré et al. [110] built a federated and sustainable framework for exchanging and using healthcare data for research purposes in FAIR (Findable, Accessible, Interoperable, and Reusable) principles [111]. The framework was built upon existing national and international terminologies (e.g., SNOMED CT [25] or LOINC [112]), with a simple “grammar” (subject-predicate-object expressed in RDF).

In Adel et al. [113], a fuzzy ontology-based SI infrastructure for distributed EHRs was developed and deployed. The first step was to create a unique local ontology for each input source. In order to combine the locally created ontologies, a consolidated ontology was created. This clear ontology, however, was unable to respond to ambiguous or imprecise questions. The consolidated crisp ontology was thirdly expanded by the authors utilizing a fuzzy logic methodology. Reda et al. [114] proposed a way for collaborating in the integration of disparate health data using SW and Linked Open Data technologies. To construct a common context-aware resource graph, the built framework was put to the test, utilizing information received from different IoT fitness vendors. In Freedman et al. [115], a unique fix was put forth in the form of an open-source Semantic Engine (SE). The application of semantically rich models to datasets was a broad objective behind the development of the RDF data transformation tool. Ontologies, models, and data sources from various fields are all compatible with the SE. The SE employed a series of instructions to simply and transparently assess the transformation of clinical data into a more sophisticated semantic model.

Yu and Dong [116] provided a structure for incorporating several healthcare data suppliers. The authors combined cutting-edge big data technologies, including NoSQL databases, Kafka, and MapReduce, with SW technologies using a hybrid architecture. To create triples of RDF, they developed a semantic lifting engine, and they then kept them in the Virtuoso RDF repository [117].

Carbonaro et al. [118] employed an ontology-based architecture, allowing SI between various IoT fitness gadgets and simplified data sharing. Pacaci et al. [119] developed a method for semantically transforming dataset sources into RDF and loading the modified data into a final repository to extract data from EHRs. In Ethier et al. [120], a TRANSFoRm core ontology was created to handle SI across diverse biomedical datasets. Infrastructural support for an LHSC in primary care in Europe was provided by that project. It was applied in around 5 systems across 4 nations, and it utilized a local-as-view data mediation approach that combined the terminological and structural models into a single framework. Jabbar et al. [121] offered SI among IoT heterogeneous devices, and an IoT-based SI Model (IoT-SIM) has been developed. Ullah et al. [122] effectively communicated SI between data generated from various healthcare systems, and the SI Model for Big-Information in IoT (SIMB-IoT) was introduced. In this investigation, data from two combined datasets were collected. From SIDER 4.1, the drug side effects dataset was gathered [123]. The authors utilized big data annotations, kept the data in RDF, and utilized SPARQL to query the RDF graphs data. SCHOPPENHAUER et al. [124] described methods for bridging the semantic divide between user-oriented views and data that is present in raw form using ontology-based data access (OBDA). Data could be made available as virtualized or materialized RDF triples that are prepared for processing and querying based on mappings between entities of data schemas and ontologies. Table 13 analyzed

Table 13 Articles that adopted SW technologies in achieving interoperability in distributed EHRs

Ref., Year	Adopted approach	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
[110], 2023	Ontology	Technical, Semantic	✓	✓	✗	✓	✗	✗	✓
[113], 2021	Fuzzy ontology	Structural, Semantic	✓	✓	✗	✗	✗	✓	✓
[114], 2021	Ontology	Semantic	✓	✓	✗	✗	✓	✗	✓
[115], 2020	Ontology	Structural, Semantic	✓	✓	✗	✓	✓	✗	✓
[116], 2019	Ontology	Semantic	✓	✓	✗	✗	✓	✗	✓
[118], 2018	Ontology	Semantic	✗	✗	✗	✓	✗	✗	✗
[119], 2018	Ontology	Semantic	✓	✓	✗	✓	✓	✗	✓
[120], 2018	Ontology	Semantic	✗	✗	✗	✓	✗	✗	✓
[121], 2017	Ontology	Semantic	✓	✓	✓	✗	✗	✗	✓
[124], 2017	Ontology	Semantic	✓	✓	✗	✓	✗	✗	✓

some related studies that adopted the SW for achieving interoperability in distributed EHRs based on the suggested evaluation measures shown in Table 12.

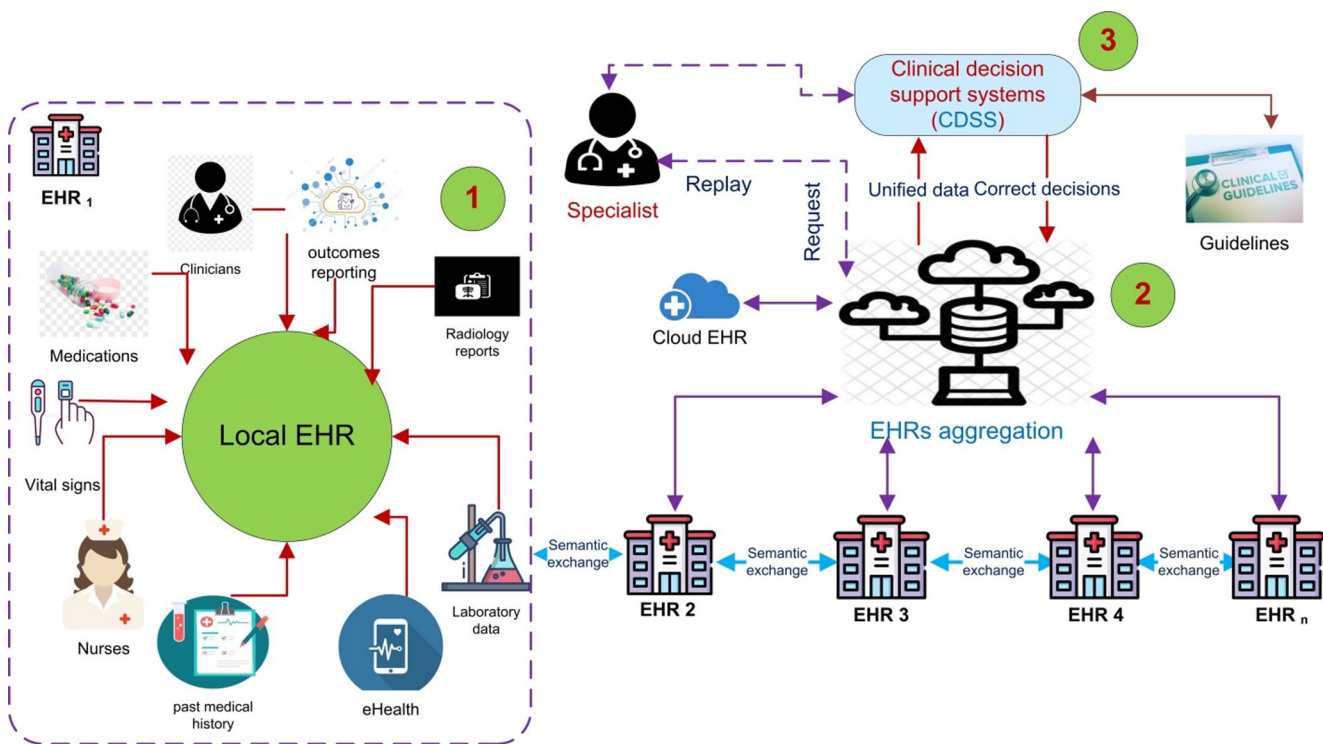
c. Learning-based approaches

The development of digital technologies presents new possibilities for more effective EHRs implementation. The large healthcare datasets' dynamic nature and complexity pose many challenges associated with storage, processing, analysis, security, usability, and data exchange [17]. Technological advancements could enhance the effectiveness of EHRs implementation in numerous ways. NLP techniques [125], machine-learning [126], rule-based, or deep learning-based [127], could read out information from unstructured data and other clinical narratives in EHRs, allowing secondary research. Learning-based approaches here mean the integration of technologies like IoT, cloud, Blockchain, ML, DL, etc. In this part, we manipulate some screened articles based on learning-based approaches adopted in solving EHRs interoperability problems. For example, Wang et al. [128] developed a 5-year risk prediction model for patients with type 2 diabetes who may experience the onset of end-stage renal disease (ESRD). Numerous ML classifiers, including logistic regression, random forest, and support vector machine, were used to classify the medical data. Vazirani et al. [129] proposed a cloud-based medical record related to data retrieval instructions and viewing permissions employing Blockchain to record interactions of patients through smart contracts. GOHAR et al. [130] showed a five-tiered architecture with cooperative elements that were created for the real-world implementation of a patient-centric framework. A layering diagram, system context, and comprehensive reference architecture are also used as the foundation for the implementation and design sides. Liu et al. [131] demonstrated how DL models for text categorization might be created using FHIR exemplification of unstructured EHR data. The authors used a case study using two obesity datasets and extended the NLP2FHIR clinical data normalization. On both raw text inputs and NLP2FHIR, they evaluated many DL-based text classifiers, including text graph convolutional networks and convolutional neural networks (CNN). Ahmed et al. [132] suggested new approaches to de-identify textual data relying on a stacked recurrent neural network (RNN). Fusco et al. [133] carried out a SWOT analysis of the adoption of SARS-CoV-2 infection and a Blockchain-based prediction model. Jamil et al. [134] suggested a novel drug outfit series management utilizing hyper-ledger fabric relying on Blockchain.

Pattanayak et al. [135] offered smart data access data-virtualization technology that allowed real-time unified access to a vast volume of data from diverse data sources. Georgi et al. [136] presented a middleware for Android that could access sensor data without worrying about the connection protocol. Zhang et al. [137] presented a Blockchain-based infrastructure dubbed FHIRChain, whose architectural decisions were intended to satisfy the key technical requirements outlined by the ONC interoperability roadmap. Hussein et al. [138] developed a genetic algorithm technique to optimize the queuing optimization technique as well as a discrete wavelet transform for enhancing overall security. Table 14 analyzed some of those related studies based on the suggested evaluation measures shown in Table 12.

Table 14 Brief of articles that adopted new approaches in achieving interoperability in EHRs

Study, Year	Adopted approach	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8
[128], 2022	3 ML classifiers, FHIR standard	Structural	✓	✓	✓	✗	✓	✗	✓
[129], 2022	Blockchain	Structural	✗	✗	✗	✗	✗	✗	✗
[130], 2022	Blockchain, Cloud, IoT	Structural	✗	✗	✗	✗	✓	✗	✗
[131], 2021	DL models	Structural	✓	✓	✓	✗	✓	✗	✓
[132], 2020	RNN	Structural	✓	✓	✓	✗	✗	✗	✓
[133], 2020	Blockchain	Structural	✗	✗	✗	✗	✓	✗	✗
[134], 2019	Blockchain	Structural	✓	✓	✗	✗	✗	✗	✓
[136], 2018	IoT paradigm	Structural	✓	✓	✗	✗	✗	✗	✓
[137], 2018	Blockchain	Semantic	✓	✓	✗	✗	✓	✗	✓
[138], 2018	Blockchain, Discrete Wavelet Transform	Structural	✗	✗	✗	✗	✓	✗	✓

**Fig. 14** From local-hosted EHRs to comprehensive global health

5.2 Globally hosted EHRs

Shared-EHR systems are established to facilitate integrated shared care within a “community of care” [92]. These shared EHRs systems could be regional or national. Global health has been defined [139] as “an area of study, research, and practice where promoting health and health equity for everyone worldwide is a top priority. The universal plan on digital health 2020–2025, which established a framework to improve digital health both nationally and internationally, was adopted in 2020 [42]. Figure 14 shows overall transactions from local-hosted EHRs to global EHRs. The main objective is to enable stakeholders and countries to move towards universal health coverage. That needs to establish a restricted management approach of new techniques and methods, and expand digital health services. Digital technologies such as CDSS, mobile wireless technologies, cloud computing, and many others have the potential to widen access to medical data. In the following, we discuss some related studies focused on achieving global EHRs.

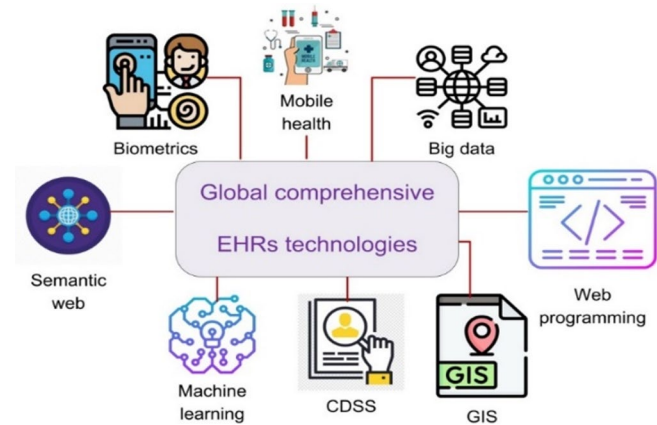
In TAPSOBA et al. [140], a SI framework that utilized a mediation technique was proposed. A knowledge base, a referential ontology that served as a semantic repository, web services, local domain ontologies for each HIS, and a referential ontology were all deployed by the mediator. Bahmani et al. [141] created a PHD (personal health dashboard). It is an open-source software architecture for storing, organizing, processing large datasets, and providing real-time data analysis at both the cohort level and the individual level that could be simply adapted to any health big data project. Horn et al. [142] described the use of thematic architecture by Gensheimer et al. [143], informed by the users' guide [144], to conceive of and put into practice a broad-based EHR-integrated strategy for PROM (Patient Reported Outcome Measures) collection throughout the orthopedic surgery division of a significant academic medical facility. Li et al. [145] presented MixEHR, a multi-view Bayesian model. Vaid et al. [146] built a model using aggregate information from five sites and a federated model that used participating parameters and a centric aggregator. Min et al. [147] conducted a semantic comparison of archetypes in 2 clinical data registries for acute coronary syndromes (ACS) from New Zealand and China. Clarke et al. [148] built a network of hospitals that depended on the frequency of patient sharing across hospitals that were divided into ten different data-sharing communities using the Louvain algorithm [149]. Table 15 compares related studies concerned with global EHRs integration. As shown in Fig. 15, there are many different technologies relevant to CDSS within the context of global EHRs.

6 CDSS interoperability

Contemporary research increasingly agrees that the effectiveness of CDSS is fundamentally constrained by the quality of healthcare data interoperability within the ecosystem rather than by sophistication alone. For example, Torab-Miandoab et al. demonstrate in their systematic review that the lack of interoperability between heterogeneous data leads to fragmented patient data, which results in various medical errors and negatively affects care delivery. They emphasize the importance of technical standards such as FHIR, HL7, and SNOMED CT to facilitate data exchange. Grob et al. (2025) [150] build on this perspective and show that standards-based

Table 15 Brief description of studies concerned with global EHRs integration

Ref, Year	Study focus	Technologies involved	Standards or SW assessment	Integration classification	Study sample
[140], 2021	Semantic mediation infrastructure	WSDM Knowledge base Referential ontology	Yes	Platform	HIS in Burkina Faso
[141], 2021	Scalability Security Interoperability	ML clusters SSH File Transfer Protocol (SFTP) PHD open-source framework	No	Platform	Cases of COVID-19 and variations in biological insulin resistance.
[142], 2021	Fully EHR-integrated	Standardized PROMs (Patient Reported Outcome Measures) collection initiative	No	Retrospective evaluation	18 adult clinics, including 4 hospital-based and 14 ambulatory clinics.
[146], 2021	Federated learning technique	Logistic regression Multilayer perceptron	-	Federated learning	COVID-19 from five Mount Sinai Health System (MSHS) institutions in New York City's EHRs.
[147], 2021	SI in different countries	openEHR archetypes	Yes	-	Chinese and New Zealander registries for the acute coronary syndrome (ACS).
[145], 2020	heterogeneous EHRs collections predicting undiagnosed phenotypes	Multi-view Bayesian model	Yes	MixEHR probabilistic model	MIMIC-III, Quebec Congenital Heart Disease, and Mayo Clinic Bipolar Disorder datasets.
[148], 2018	Inter-organizational patient-sharing connections Improve the cost-effectiveness	Louvain algorithm Python Geographic information systems	No	Platform	Hospital attendance in England from 2013 to 2015.

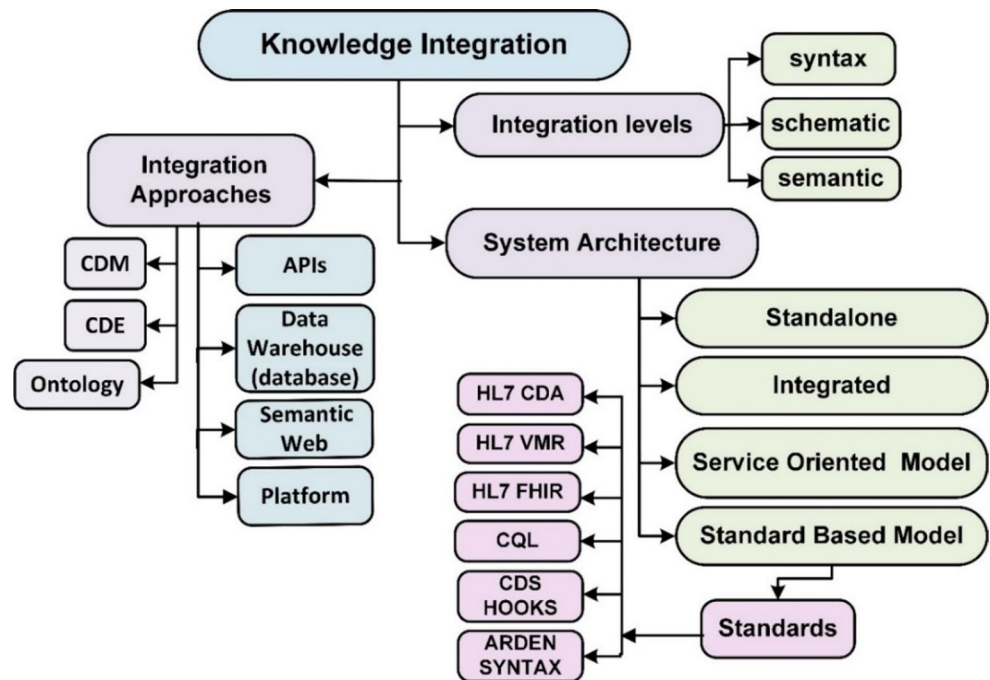
Fig. 15 Technologies-enabled global health integration

interoperability can be operationalized in real clinical environments through the use of openEHR and CDS to support guideline-driven decision-making across various healthcare systems in different hospitals. Within this interoperable context, the integration of various health records demonstrates important clinical benefits. Murthi et al. (2024) [151], in a comprehensive review, confirm that EHR integration with digital technologies such as CDSS alerts, real-time decision support, and predictive analysis can reduce medical errors and adverse drug events among hospitalized adults, despite persistent implementation challenges related to data integrity concerns and clinician acceptance. From an analytical standpoint, Lee et al. (2024) [152] provide advancements by introducing the Multiple Embedding Model for EHR (MEME). It is a deep learning framework that converts tabular EHR data into pseudo-notes and applies multi-stream embedding with self-attention, achieving promising predictive performance. At the macro level, Abdelaziz and Rosa (2024) [153] provide a bibliometric analysis showing that research on CDSS integrated with EHR has grown, with increasing emphasis on machine learning, artificial intelligence, and diagnostic support. Yet, the field remains limited in terms of long-term organizational and economic impact. Fernandes Prabhu et al. (2025) [154] mention that the next generation of decision support integrates artificial intelligence with EHRs, wearable devices, and patient-reported outcomes to enable predictive, patient-centered care, while emphasizing trust, transparency, and explainability. These studies indicate that sustainable progress in CDSS requires the co-evolution of interoperable infrastructures, intelligent analytics, and human-centered design within complex healthcare systems.

According to HIMSS, an HIS must be able to create a comprehensive picture of the clinical record during a patient meeting [3]. Therefore, it is clear that having an integrated support component is essential for an HIS to function well in terms of decision-making processes. An infrastructure for integrating clinical data from patient care with medical research data has been developed by several organizations, both inside and outside of hospitals. Data integration centers (DICs) have been identified as the key element in addressing this dilemma. At each participating hospital, offering a variety of services, they should set up the technological and administrative infrastructure. These include data harmonization, integration, and standardization. This section discusses the CDSS interoperability according to proposed architectural interoperability directions (i.e., interoperability of CDSS with EHR and interoperability of CDSS with CDSS), which are concerned with data-knowledge sharing and knowledge-knowledge sharing. Figure 16 shows different CDSS integration perspectives, which we could use to distinguish various CDSSs. These dimensions are integration level, which is based on interoperability level, integration approach with either CDSSs or EHRs, and system architecture.

As represented in the proposed interoperability types, CDSS interoperability is based on the interoperability of CDSS with EHRs and the interoperability of different CDSSs. Table 16 represents a review of works of literature that focus on CDSS-EHR or CDSS-CDSS integration. It compares such works according to several CDSS integration and interoperability technological and implementation dimensions that were previously discussed.

Fig. 16 Different knowledge integration perspectives



Those dimensions are interoperability level, system integration architecture, and knowledge management and representation approaches.

6.1 CDSS integration architectures

Four alternative software architecture models are available to develop CDSS systems [13, 20, 73, 189]. The primary aspects that affect the choice of this architectural model are time, the amount of available resources, the degree of interaction with other health systems, and the level and simplicity of software component reuse. These architectural models with similar technical characteristics are:

- A standalone architectural model, in which ACDSS has no integration with an external EHR or HIS.
- Standard-based architectural model.
- Service-oriented model, in which a CDSS is separated from the EHR or HIS but is integrated via service-based interfaces.
- An integrated model, in which there is a tight coupling between a CDSS and the EHR or HIS.

6.2 Integration approaches

Health data integration approaches could be classified according to utilization approaches. These approaches, which are declared in Fig. 15, are APIs, the semantic web, data warehouses, and federated frameworks. These utilization-based classifications are not perfect, as there is an overlap between web service, composition, and API platforms [20].

APIs with Manual Alignment: According to this categorization, healthcare data is collected from many sources via APIs, and after that, manual alignment is carried out to merge the data from diverse data models. Additionally, it suggests that there are no inherent semantics in the process or the integrated data, setting it apart from the semantic web's categorization. Typically, this type of integration moves forward dynamically, which means the data is not stored by the integration technique.

Table 16 Literature about EHR- CDSS or CDSS-CDSS interoperability and integration

Ref.	Integration Approach (Sharing Schema)	System Architecture	CDSS Type	Interoperability Level	Integration (Interoperability Type)	Clinical Problem	CDSS Rule Representation Language	Rule Engine (Reasoning)	Standards	Dataset
[155] (2017)	CDE	Standalone CDSS	Expert Knowledge-based CDSS	Structure	EHR-CDSS	Diagnosis of heart diseases	Fuzzy rules	Fuzzy Inference	--	Heart hospital in Tehran
[156] (2017)	Ontology	Standalone CDSS	Evidence-based knowledge-based CDSS	Semantic	EHR-CDSS	Clinical management of comorbidities	OWL-DL	Pellet	--	Medical records relevant to CHF and AF
[157] (2017)	Ontology	Modular CDSS system (inference, ranking, reasoning)	knowledge based CDSS	--	EHR-CDSS	Antidiabetic medication	Jena rules, Fuzzy rules	Jena inference engine	--	--
[158] (2017)	Ontology	-Web services based CDSS, API for EMR	knowledge based CDSS	Semantic	EHR-CDSS	Chronic disease, CPGs of T2DM and HT	Jena	Jena reasoner + SPARQL	HL7	--
[159] (2017)	Single ontology	Service-oriented CDSS	Knowledge-based CDSS	Semantic	EHR-CDSS	Chronic disease management	Jena rules, RDF	Pellet	HL7	Real dataset from follow-up evaluation records of type 2 diabetic patients.
[160] (2017)	CDM+ Ontology	-API CDSS architecture with Single data warehouse	Knowledge-based CDSS	Semantic	EHR-CDSS	Linking pharmacovigilance evidence sources with clinical data	RDF	--	OHDSI framework (OMOP, MeSH, MedDR, RxNorm)	--
[161] (2017)	CDM + Ontology	Client-server CDSS architecture with a single data warehouse	Knowledge-based CDSS	Semantic	EHR-CDSS	Evidence-based public health (EBPH)	Description logic	reasoners (Fact++, Pellet)	--	CMA of Montréal, Québec, Canada.
[160] (2017)	Ontology	Service-oriented CDSS	knowledge based CDSS	Semantic	EHR-CDSS	Chronic diseases	OWL ontologies, RDF triples, and SW (SPIN) rules.	Pellet, Aleph, Jena, SWI Prolog	--	Real dataset of patients with hepatitis
[162] (2017)	Ontology	Service-oriented CDSS	knowledge based CDSS	Semantic	EHR-CDSS	Automatic triage assessment	OWL	Pellet	--	--
[163] (2017)	CDM	Loosely integrated CDSS	Rule-based CDSS	Semantic	EHR-CDSS	Treatment quality control	Archetype	logical inference engine, fuzzy logic inference	openEHR	Treatment data from Hospital in Tomsok
[164] (2018)	Ontology + CDM	Modular web Service oriented CDSS	Case-based CDSS	Semantic	EHR-CDSS	Breast Cancer Patients	N3	Euler/EYE inference engine	FHIR	--

Table 16 (continued)

Ref.	Integration Approach (Sharing Schema)	System Architecture	CDSS Type	Interoperability Level	Integration (Interoperability Type)	Clinical Problem	CDSS Rule Representation Language	Rule Engine (Reasoning)	Standards	Dataset
[165] (2018)	CDE	Modular Standalone CDSS	Knowledge-based CDSS	--	EHR-CDSS	Interpretation of laboratory test results	First-order predicate logic.	Their engine	--	--
[72] (2018)	CDM	Client-server CDSS	Knowledge base CDSS	Semantic	EHR-CDSS CDSS-CDSS	Automated (SIRS) detection in pediatric intensive care	Rules	Drools2	openEHR Archetype, LOINC terminologies, AQL queries	Hannover Medical School (HaMSTR) Data Repository
[166] (2019)	Single ontology (FASTO, SSN, BFO)	Cloud-based CDSS	knowledge based CDSS	Semantic	EHR-CDSS	Monitors and manages type 1 diabetes mellitus	SWRL	Rule-based reasoner (Pellet)	HL7 FHIR	--
[167] (2019)	Ontology (CIG-IntO)	Client-server CDSS	Evidence-based CDSS	Semantic	EHR-CDSS	Comorbidity	OWL2, First Order Logic (FOL).	Jena Reasoner, SWRL, OWL 1 DL, OWL DL+, OWL 2 DL	--	--
[168] (2019)	CDE	Web-based CDSS	Rule-based CDSS	DATA	EHR-CDSS	Prescription of Antibiotic drugs	CPG, rule-based module	--	--	Erasmus MC
[169] (2019)	Ontology	Service-oriented CDSS architecture	Rule-based CDSS	Semantic	EHR-CDSS	--	--	Rule engine, Bayes engine	FHIR LOINC, SNOME CT, CDS HOOKS	--
[170] (2019)	CDM	Integrated Web service-based CDSS.	Knowledge-based CDSS	Semantic	EHR-CDSS	PDDI, Digoxin Cyclosporine, and Warfarin-NSAID	CQL	CQL engine, FHIR clinical reasoning module	CDS Hooks, FHIR, CQL	--
[171] (2020)	CDE	DLI-CDSS was integrated into the CPOE.	Rule-based CDSS	Data	EHR-CDSS	Kidney transplant clinic	IF&THEN rules	--	--	Collected real patients' data
[172] (2020)	Disease ontology	Standalone CDSS	Knowledge base CDSS	Semantic	EHR-CDSS	Oncology pharmacotherapy	--	--	Public standards	Clinical Trials.
[173] (2020)	Ontology + CDM	Web-based CDSS	Knowledge-based CDSS	Semantic	EHR-CDSS	two use cases: implementation of two colorectal cancer screening protocols; clinical laboratory test results semantic publishing	OWL archetype	OWL reasoner	SW standards	Real EHR system deployed in Spain.
[174] (2021)	CDE	Integrated client-Server CDSS architecture	Knowledge-based CDSS	Semantic	EHR-CDSS CDSS-CDSS	SIRS detection in (PICU).	AQL	--	OpenEHR, (LOINC)	Open data platform

Table 16 (continued)

Ref.	Integration Approach (Sharing Schema)	System Architecture	CDSS Type	Interoperability Level	Integration (Interoperability Type)	Clinical Problem	CDSS Rule Representation Language	Rule Engine (Reasoning)	Standards	Dataset
[175] (2022)	CDM	Integrated modular Service-oriented CDSS.	Rule-based CDSS	Semantic	EHR-CDSS	DDInteract between an anticoagulant (warfarin) and (NSAIDs) interactions	CQL	--	HL7 FHIR CDS Hooks	Epic
[176] (2022)	CDM	Integrated standards-based server architecture, Cloud-based Amazon Web Services	Rule-based CDSS	Semantic	EHR-CDSS	PHM, familial cancer risk case study	CQL	--	HL7, CQL, FHIR, and CDS Hooks	Three large health-care organizations (UHealth), (NYU), and Intermountain Healthcare
[177] (2022)	CDM	-client-server CDSS architecture	Rule-based CDSS	Semantic	EHR-CDSS	--	--	--	openEHR	--
[178] (2022)	Ontology	REST API CDSS	Knowledge-based CDSS	Semantic	CPOE-EHR, EHR-CDSS	Reduce medication errors	Protege-OWL	--	--	Three datasets (AQuAS), ABX dosage
[179] (2018)	CDM+ CDE	Tightly coupled CDSS	Non-Knowledge based CDSS	Semantic	EHR-CDSS	Investigate DL in a variety of Prediction problems	--	--	FHIR	EHR data from the University of California, LSDB
[180] 2019	CDE	Loosely integrated CDSS	probability-based ML CDSS	Data	EHR-CDSS	Patient-specific diagnosis: breast cancer metastasis	If/then statements	Variables-based Bayesian networks.	--	--
[181] (2019)	CDM	Service-oriented CDSS	Non-knowledge CDSS	Semantic	EHR-CDSS	Hemoglobin reference intervals, Predicting colorectal cancer outcomes	--	--	OMOP-CDM, FHIR	A 300 colorectal cancer patients Synthetic dataset
[182] (2019)	CDM	Modular standalone CDSS	ML CDSS	Semantic	EHR-CDSS	Identify patients with obesity and their comorbidities.	--	--	HL7 FHIR	The i2b2 obesity Challenge dataset, MIMIC-III obesity
[183] (2020)	CDM+ CDE	Standalone CDSS	AI-based CDSS	Semantic	EHR-CDSS	Prediction of disease	--	--	OpenEHR, nephrology dataset	ORBDA
[184] (2020)	CDE	Standalone or EHR-integrated CDSS	ML CDSS	Data	EHR-CDSS	Patient-specific disease: Parkinson	(LR), (SVM-RBF), (SVM-L), (RF), (NN), and (GB)	--	--	Health Fact
[185] (2021)	Ontology	Modular CDSS	Rule and machine learning-based CDSS	Semantic	EHR-CDSS	Chronic kidney disease	A causal chain of abnormal states	a causality inference based on the causal chain.	--	EHR from the University of Tokyo Hospital
[186] (2022)	CDM+ CDE	API-based CDSS integration	knowledge- and nonknowledge-based CDSSs	Semantic	EHR-CDSS	Sepsis treatment	--	--	OMOP, CDM, HL7 FHIR CDS Hooks	--

Table 16 (continued)

Ref.	Integration Approach (Sharing Schema)	System Architecture	CDSS Type	Interoperability Level	Integration (Interoperability Type)	Clinical Problem	CDSS Rule Representation Language	Rule Engine (Reasoning)	Standards	Dataset
[187] (2022)	CDE	Integrated CDSS	AI-based CDSSs	achieved	EHR-CDSS CDSS-EHR	Management of COVID-19 patients	--	--	Standardized	patients with SARS-CoV-2 infection
[188] (2023)	CDE	Stand-alone CDSS	Machine learning-and Rule-based CDSS.	Data	EHR-CDSS	Detection of patient allergies	Clinical language model	--	--	Hospital integrated EHR system

CDE: Common Data Element; CDM: Common Data Model; OWL-DL: Web Ontology Language Descriptive Logic; AF: Atrial Fibrillation; CHF: Chronic Heart Failure; EMR: Electronic Medical Record; T2DM: Type 2 diabetes mellitus; HT: Hypertension; CPGs: Clinical Practice Guidelines; CMA: Census Metropolitan Area; SIRS: systemic inflammatory response syndrome; SSN: semantic sensor network; BFO: basic formal ontology; PDDI: Potential drug-drug interactions; CQL: Clinical Quality Language; CPOE: Computerized physician order entry; CIG-IntO; PICU: pediatric intensive care unit; DDInteract: drug-drug interaction; PHM: Population health management; UHealth: Utah Health, NSAIDs: nonsteroidal anti-inflammatory drugs; NYU: New York University Langone Health; Nomenclator for prescription, LSDB: The Lynn Sage Data Base; i2b2: Informatics for Integrating Biology and the Bedside; ORBDA: Open EHR Benchmark Dataset; LR: Logistic regression, SVM-L: linear support vector machine; SVM-RBF: support vector machine with RBF kernel; NN: neural network, RF: random forests; EBPH: evidence-based public health; CPG: Clinical practice guidelines AQuAS: Agency for Health Quality and Assessment of Catalonia

Semantic Web: This categorization makes use of SW technology to combine health data from many sources and improve the semantics of the combined data or the integration process. Such methods typically require extra semantic annotations or other processing on the data sources.

Platform: This classification could be regarded as an improved form of APIs with manual alignment classification. Personal Health Record (PHR) systems form some of the platform approaches, but from the data integration point of view, we categorized them as platform approaches.

Data warehouses: They hold data in a single location without any real integration.

To address the problems of data heterogeneities, many conventional data integration systems have been created based on common data models (CDMs) and common data elements (CDEs) [190, 191], such as data warehouses or federated frameworks [192]. A data integration system should choose between either of these approaches (or a hybrid architecture), depending on the project's objectives and the availability of the data that has to be merged. These conventional approaches for data integration, while effective in resolving the heterogeneity of syntactic and schematic data, fail to capture the semantics of the data or its meaning and context.

With the development of semantic technologies, the idea of semantic data integration (SDI) has received greater attention, and SDI methods are being used more often to make it easier to integrate data from many sources [193]. Three distinct data integration strategies (CDMs), (CDEs), and ontologies with varying degrees of ability for integrating semantics across various data sources were found by Zhang et al. [21].

The relationships between the data elements are not depicted in research that employs CDEs as the global schema; instead, they can only give the semantics of the data items. Similarly, relationships between various data elements can also only be partially captured when a CDM is used as the global schema. As a result, neither CDMs nor CDEs offer any computational semantics since neither one of them offers an effective method to assign or validate the meaning of symbols. On the other hand, research that used an ontology-based approach was able to not only handle definitional disagreements but also include restrictions and relationships between the variables in the ontology.

6.3 Data- knowledge interoperability (EHR-CDSS)

CDSSs encompass various systems such as tools to warn clinicians of problematic states, complex platforms to store and manage clinical data, or decision-making tools. Regardless of the type of decision-support task, a CDSS should interact with other components and be seamlessly incorporated into the clinical information system. Despite decades of research, the majority of CDSSs lack interoperability capabilities. One of the grand challenges of CDSS is to propagate existing CDSS knowledge by building an architecture for sharing executable CDSS modules. EHR systems vendors typically have rules libraries that only work in their systems and employ their exclusive data dictionaries and models. This is because the predominant method of CDSS rule customization for each EHR is demonstrated by the “curly braces problem”. The integration of vendor HIT solutions with external CDSS requires a lot of work since the sharing and integration of knowledge across various platforms has been limited [32]. A possible methodology is to build a canonical information model that is utilized by both the knowledge artifact scan and the knowledge source systems. This approach eliminates the need to map CDSS variables to local data or develop a set of specific rules to access the local data in every situation.

The central goal of a sharable CDSS module for an EHR is to be able to subscribe to these services while allowing healthcare organizations to implement their interventions with little extra effort. A crucial component of this challenge is to determine and standardize both the definitions and interfaces of the required data by different CDSS modules [81]. It can be observed that a stand-alone CDSS needs a large amount of input and will not be used regularly, due to its cumbersome nature. On the other hand, the restricted concentration of most systems implies that they will only be needed in rare situations, at which point the simplest answer may be to skip them altogether in favor of alternative decision-support techniques. Integrating CDSSs into EHR systems has been demonstrated to increase clinical care quality, patient outcomes, and medical professional adoption [194]. These two systems' integration also enables the CDSS to access historical patient data for its inferencing requirements

and save any data it can return into the EHR. As a result, unnecessary data entry and errors brought on by entering incomplete or wrong data are reduced. Other benefits of the integration between the two systems include a single sign-on and uniform user interfaces [195].

6.4 Knowledge interoperability (CDSS-CDSS)

The deployment and usability of workflow integration in complicated healthcare environments have a significant impact on CDSS effectiveness. However, the majority of CDSSs were created for healthcare providers. They did not completely consider the variety of providers, their needs, and their degrees of experience. When employing CDSS, medical professionals may anticipate making decisions more quickly and accurately and hope to take care of their patients in a better way [81]. CDSS usually utilizes data from various sources. Thus, developing a complete and consistent CDSS is challenging. The importance and effectiveness of a CDSS depend significantly on the usefulness of the CDSS rules. Since it is very costly to build these rules from scratch each time, it is ideal to reuse and share CDSS rules. However, this approach is not common practice across organizations. Unfortunately, most real-world systems are created with a certain objective in mind (like diagnosing breast cancer). Therefore, it would be difficult or impossible to utilize them for other purposes.

For the CDSS to remain up-to-date and useful in facilitating the delivery of clinical care, it must be updated often as part of an EHR system. However, it demands a huge amount of time and resources for creating, managing, keeping, sharing, and reusing CDSS rules. Larger institutions, which often have more resources than small-scale practices, have recognized this resource-demanding process.

Although CDSS have demonstrated their effectiveness in clinical care, the sharing and reusing of CDSS rules have not been accomplished. The development of standardized methods for information exchange for CDSS is one of the most active areas of research nowadays. The continuous development and usage of universal standards created to meet CDSS requirements in the healthcare industry would facilitate CDSS functionality and exchange.

6.5 Data privacy and security considerations

Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) are two of the regulatory frameworks that mandate the health information safety [157, 158]. The difference between HIPAA and GDPR is that HIPAA maintains the protection through privacy and security rules, as well as technical safeguards to ensure data integrity. While GDPR provide requirement for personal data processing, including transparency, accountability, purpose limitation, and lawfulness. Our proposed architecture (three-level interoperability) is mainly designed to facilitate compliance with regulations through a layered model. For the first layer (EHR_EHR interoperability layer) [159], all data transmitted between EHR systems should be encrypted with a string encryption protocol. Then, attribute based access control mechanism should be utilized to ensure that data is shared according to patient consent [160], role, and context of care. Second layer (CDSS_EHR interoperability), the integration between CDSSs and EHR should occur according to Secure API (FHIR, HL7, etc.) [161]. FHIR provide built in security features which handle authentication and authorization issues. Third layer (CDSS_CDSS interoperability layer). This layer mainly exchanges knowledge (rules, models, etc.), the architect must ensure the integrity of shared clinical knowledge [162, 163]. Utilizing a digital signature as well as hashing could verify the originality of the knowledge.

7 Limitations and future research directions

This review is directed to architectural approaches for health data interoperability, aiming to provide a complete view to achieve integration. However, several limitations remain that open promising avenues for further research. Those limitations are featured as follows:

1. **Explainable AI trustworthy interoperability:** Another rich research direction is explainable AI and hybrid systems that combine various CDSS types. Because interoperability and explainability are closely related concepts, researching cause and effect inside an integrated system can help decision-makers produce more precise and flexible results.
2. **Adaptive interoperability frameworks** are capable of dynamically adjusting standards, mappings, and data exchange rules depending on clinical context, patient characteristics, or system workload. This would enhance flexibility and reduce integration bottlenecks in heterogeneous healthcare environments.
3. The use of **blockchain technologies** and **federated learning** represents a rich area for exploration: blockchain can guarantee secure, tamper-proof, and auditable data sharing, while federated learning allows CDSS models to be trained across multiple institutions without moving sensitive patient data, thereby reconciling privacy with collaborative intelligence.
4. **Standardized evaluation and benchmarking metrics** remain a critical gap. Future work should establish frameworks to systematically assess interoperability in terms of latency, scalability, throughput, usability, and explainability, supported by open testbeds and shared datasets.
5. **Patient-centric interoperability and precision medicine** which require seamless integration of genomic, proteomic, and real-world evidence into EHR and CDSS platforms.
6. **Handling uncertainty in healthcare:** Much of the data gathered from various healthcare sources contains some ambiguity due to noise and lack of information [196]. To design uncertainty data models, new processes and techniques based on NLP and ML should be implemented [197, 198].
7. **Public health EHR content standardization:** Achieving interoperability across heterogeneous and global HISs requires clear standardization frameworks and implementation guidelines [199]. More research is needed to investigate how standardized EHRs could be utilized in ML-based CDSS to ensure consistency, accuracy, and transferability of knowledge across diverse healthcare settings.
8. **Providing a complete and comprehensive view of all the approaches.** While this review highlights various approaches to interoperability, there is still a need to unify them under a comprehensive architectural framework. Standards can use and exchange EHRs data in a coordinated way across organizational and regional boundaries [200]. Additionally, the integration of data silos through the semantic web could raise the quality of care. Healthcare decision-making frequently requires cross-institutional collaboration and information sharing [201]. On the other side, interoperability is now a critical component of AI and ML development, allowing smaller providers to access data resources once only available to tech giants [202].

8 Conclusion

Information integration is an urgent need to support a united view of all healthcare data. That integration entails the consolidation of all distributed patient data into a single integrated system. Wherever and whenever necessary, it provides doctors and specialists with thorough medical information on the patients, which results in effective therapy. This review summarizes the existing survey studies concerned with interoperability in EHRs or CDSS. It manipulates the possible approaches of integration in distributed EHRs and different CDSSs. It introduces a new interoperability classification between EHRs data and CDSS knowledge. We move towards achieving global EHRs, which can access patient data from any location at any time, and thereby achieve more efficient overall healthcare. In future work, we will continue to facilitate health data.

Beyond its conceptual contributions, the proposed interoperability framework also offers several **practical applications**. For example, **national health information exchanges** could employ the classification to promote unified integration across institutions and regions. Similarly, **hospital networks and multi-center research collaborations** stand to gain from smooth EHR–CDSS interoperability, enabling coordinated diagnosis and shared treatment strategies. In addition, **public health monitoring and population health programs** may leverage

CDSS–CDSS interoperability to align distributed decision-support tools for managing chronic diseases, ensuring drug safety, and responding to epidemics. Collectively, these applications highlight the significance of architectural interoperability approaches in advancing patient-centered healthcare and reinforcing the resilience of health systems.

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Declarations

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