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# ARCHITECTURAL HEALTH DATA STANDARDS AND SEMANTIC INTEROPERABILITY: A COMPREHENSIVE REVIEW IN THE CONTEXT OF INTEGRATING MEDICAL DATA INTO BIG DATA ANALYTICS.

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*Abstract:* **The integration of medical data into Big Data analytics holds significant potential for advancing healthcare practices and research. However, achieving semantics interoperability, wherein data is exchanged and interpreted accurately among diverse systems, is a critical challenge. This study explores the impact of existing architectures on semantics interoperability in the context of integrating medical data into Big Data analytics. The study highlights the complexities involved in integrating medical data from various sources, each using different formats, data models, and vocabularies. Without a strong emphasis on semantic interoperability, data integration efforts can result in misinterpretations, inconsistencies, and errors, adversely affecting patient care and research outcomes. The significance of data standards and ontologies in establishing a common vocabulary and structure for medical data integration is underscored. Additionally, the importance of data mapping and transformation is discussed, as data discrepancies can lead to data loss and incorrect analysis results. The success of integrating medical data into Big Data analytics is heavily reliant on existing architectures that prioritize semantics interoperability. A well-designed architecture addresses data heterogeneity, promotes semantic consistency, and supports data standardization, unlocking the transformative capabilities of medical data analysis for improved healthcare outcomes.**

*Keywords:-***Health data standards, Medical data, EHR integration, Semantic interoperability, Big data analytics.**

## I. INTRODUCTION

Recently, there has been interest, primarily among health system vendors, in the need for systems that enable semantic data interoperability. Various studies investigate methods for resolving compatibility issues. Adopting health standards and tools for adequate data representation, such as ontologies, databases, and clinical models that ensure healthcare workers handle the data effectively are challenging.

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healthcare workers handle the data effectively are challenging.
Interoperability in electronic health records has been supported by Mello et al. (2022) from a management and business perspective. They agree that data exchange and integration across organizational boundaries can enhance work processes, quality of care, and efficiency while lowering costs. The authors have demonstrated the connection between big data and healthcare. On the technological front, data exchange fosters personalized patient care, reduces errors, and eliminates rework. From the side of the citizens, it underlined the support for developing the fundamental public health initiatives, controlling, monitoring diseases, lowering expenses, and boosting efficiency.
On the other hand, Lee, Kim, & Lee, (2021) and Gagalova & Elizalde,(2020) analyzed technological aspects of data interchange, integration, and interoperability in EHRs. The first article depicted the advantages of adopting clinical data warehouses, which facilitate enhanced data processing, specialist analysis, and clinical research. The second article proposed a worldwide model that takes health data into account. The study suggested use of vocabularies, terminologies, and the HL7 FHIR health standard.
The authors of Adel, El-Sappagh, Barakat, & Elmogy, (2019) address the strong trend toward standardization. The writers expressed interest in using ontologies, particularly fuzzy ontologies, to analyze the literature. The research highlights characteristics that may be shared by the leading health standards and provides a thorough background to context for each of their various structures. The article used the word "electronic Health Standard" to refer to the adopted standards, whereas we stick with the more general term "health standard." Additionally, the authors outlined four trends in semantic interoperability that help in identifying issues and areas for future research. These trends include frameworks to address semantic interoperability issues, using ontologies to address interoperability issues, standards in an interoperable EHR, barriers, and the heterogeneous problem of EHR semantic interoperability.
In addition, the studies developed by Adel, El-Sappagh, Barakat, and Elmogy, (2019) and Lee, Kim, and Lee, (2021) vividly illustrated the expansion and interest of the healthcare sector in using standards for electronic medical records, overcoming organizational barriers, and achieving interoperability among healthcare providers. Given this situation, the study reviewed the adoption of standards over the past few years and the tools that eventually make up the environment for a semantically interoperable EHR.

## II. METHODS

The study conducted a systematic literature review as per the block diagram depicted in Figure 1.
Eligibility Criteria: This review targeted peer-reviewed publications, government reports and eHealth strategic documents related to health information exchange (HIE) policy and standards. The eligibility criteria such as the characteristics to be taken into account to perform the search on publications between January 2010 and 2023
Search Strategies: In order to find relevant publications related to HIE, major electronic databases of peer-reviewed journal articles, such as PubMed, IEEE Xplore and ScienceDirect were selected. The performed search queries applied the selected databases are presented in Table 1. In addition, Google and Google Scholar were used to retrieve government reports and eHealth strategic documents. Furthermore, peer-reviewed publications were identified from reference lists of relevant reviewed articles that met the inclusion criteria and these articles were retrieved using Google Scholar.
A systematic and comprehensive search was performed by two independent reviewers. The search strategy was developed after identifying keywords and combining them with Boolean operators (“AND” and “OR”). Table 1 shows the main search terms and the alternative keywords. The search terms were combined using Boolean operators to search for potential publications in relation to HIE policy and standards.

**Table 1: Search queries in databases**

| Database | Search Query |
|---|---|
| PubMed | ("electronic health records"[MeSH Terms] OR "hospital information systems"[MeSH Terms] OR "health information systems"[MeSH Terms] OR "electronic health records"[Title/Abstract] OR "electronic medical records"[Title/Abstract] OR "clinical information systems"[Title/Abstract] OR EHR[Title/Abstract] OR medical records systems[Title/Abstract] OR automated medical systems[Title/Abstract] OR "Health Information Systems"[Title/Abstract])<br>AND<br>("clinical information model"[Title/Abstract] OR "semantic interoperability"[Title/Abstract] OR “architectural framework for integration” |

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| | |
|---|---|
| | [Title/Abstract]]) AND ("2010/01/01"[PDAT] : "2023/03/31"[PDAT]) |
| ScienceDirect | (("electronic health records" OR "health information systems" OR "electronic medical records" OR "hospital information systems" OR "EHR" OR "clinical information systems" OR "medical record systems" OR "automated medical record systems") AND ("semantic interoperability" OR "clinical information model" OR “architectural framework for integration”)) |
| IEEE Xplore | (( "Abstract": “Electronic Health Record” OR "Document Title": “Electronic Health Record” OR "Abstract": “electronic medical record” OR "Document Title": “electronic medical record” OR "Abstract": “clinical information system” OR "Document Title": “clinical information system” OR "Abstract": “hospital information system” OR "Document Title": “hospital information system” OR "Abstract": “automated medical system” OR "Document Title": “automated medical system” OR "Abstract": “Health Information System” OR "Document Title": “Health Information System” OR "Abstract": “EHR” OR "Document Title": “EHR” OR "Abstract": “medical records system” OR "Document Title": “medical records system”) AND (("Abstract": “clinical information model” OR "Document Title": “clinical information model”) OR (Abstract: "semantic interoperability" OR "Document Title": "semantic interoperability") OR (Abstract: "architectural framework for integration " OR "Document Title": "architectural framework for integration”)) |

Study selection: Based on the inclusion and exclusion criteria, all searched records were transferred to Endnote X9, a reference management software, to discard duplicate studies. After duplications were removed, two reviewers independently read the titles and abstracts of the remaining articles to identify both potentially eligible articles and any articles for which a determination could not be made from the title and abstract alone. Then, the selected full text of the remaining articles was examined for eligibility. All disagreements between the reviewers were resolved through consensus.
Quality appraisal: A discussion between two independent reviewers was made prior to commencing the quality appraisals by using a random sample of 3 articles. Then, a quality appraisal was performed based on the problem statement, objective, method, citation, result usefulness, and result applicability of the articles, as shown in Appendix A. The quality of each article was measured using a 3-point scale (high, moderate and low). High-quality publications are those which have clearly defined objectives, proper citations, adequately described methods and useful results. Moderate quality publications are those whose objective, method and results are inadequately described while low quality is given for publications where any of the quality measures are missed. All disagreements in the quality of the articles between the reviewers were resolved through consensus.
Synthesis of results: A data extraction form was developed prior to synthesizing the results. The form included authors' names, year of publication, objectives, methods, and findings related to HIE policy and standards for peer-reviewed articles while a different format was used for government reports and eHealth strategic documents, see **Appendix A and Appendix B**.

## III. RESULTS

### 3.1. Study Selection
A total of 605 citations were identified through a comprehensive search from databases and search engines from which 153 of them were duplicates. A total of 284 were excluded based on the eligibility criteria previously outlined and 37 were included in the review. This was arrived at based on study selection in systematic review Mamuye, et al. (2022) as depicted in a flowchart in Figure 1.

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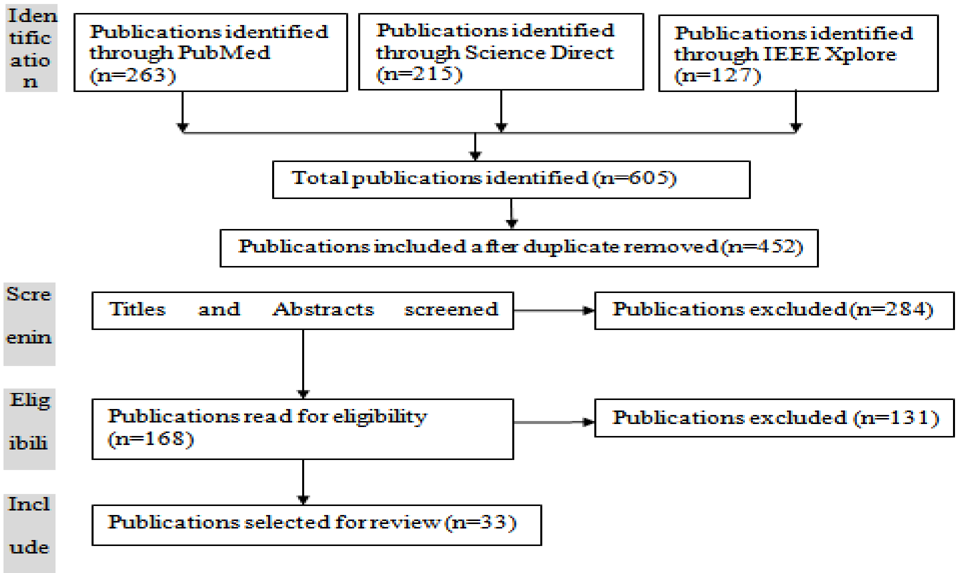


**Figure 2 : Search results and study selection flowchart**(Source Author)

**3.2 Characteristics of Studies**

Out of the 33 articles reviewed, 25 were journal articles and the remaining 8were governmental eHealth-related strategy and policy documents on the integration of medical data to big data analytics. HIE policy-related articles were 3 while HIE standard-related articles were 24 and 6 articles addressed both HIE policy and standards. Most of the articles 72.7 % had a high quality, 21.2 % had moderate quality while 6.1% hadlow quality in terms of their methods, credibility of their citation, and applicability (Appendix A and Appendix B). In terms of the study methods, 90.9% of the publications were based upon situational analysis using document reviews (e.g., World Health Organization (WHO) eHealth strategy development toolkit), 6.1% were discussion in meetings and workshops and survey and site visit had 3 %. Among the journal articles (24), 8 articles followed interoperable system design and development method, another 3 articles followed framework design in which two of them supplemented framework development with a qualitative approach (case study). 11 articles followed literature review and two article followed a consultative workshop while the remaining one followed a discussion of a specific interoperable platform

## IV. DISCUSSION

Recently, there has been increased interest in the need for systems that enable semantic data exchange, notably among health system suppliers. Several studies look on methods for fixing compatibility issues. The implementation of health standards and technology, such as ontologies, databases, and clinical models, for the purpose of ensuring effective data management by healthcare staff, poses significant challenges.

Mello et al. (2022), advocate for the enhancement of interoperability in electronic health records (EHRs) within the context of management and business considerations. They all believe that cross-organizational data exchange and integration can improve work processes, quality of care, and efficiency while cutting costs. The authors established a link between big data and healthcare. Data exchange, on the technological front, promotes tailored patient care, lowers errors, and eliminates rework. Citizens' support for creating core public health programs, regulating and monitoring diseases, cutting costs, and increasing efficiency was emphasized.

Lee, Kim, & Lee, (2021) and Gagalova & Elizalde,(2020) and Gagalova and Elizalde, (2020), on the other hand, investigated technological elements of data transfer, integration, and interoperability in EHRs. The first article discussed the benefits of implementing clinical data warehouses, which allow for improved data processing, specialist analysis, and clinical research. The second piece offered a global model that takes into consideration health data. The study recommended that vocabularies, terminologies, and the HL7 FHIR health standard be used.

Adel, El-Sappagh, Barakat, & Elmogy, (2019) discuss the strong trend toward uniformity. The authors indicated an interest in analyzing the literature using ontologies, particularly fuzzy ontologies. The study emphasizes traits that the main health standards may have in common and provides a full backdrop and context for each of their distinct structures. The term "electronic Health Standard" was used in the article to refer to the established standards,

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although we prefer the broader term "health standard." The authors also identified four patterns in semantic interoperability that aid in identifying challenges and prospects for further research. There are several emerging trends in the field of semantic interoperability that are worth discussing. These include the development of frameworks designed to solve concerns related to semantic interoperability, the utilization of ontologies as a means to tackle interoperability difficulties, the establishment of standards within interoperable electronic health record (EHR) systems, the identification of hurdles that need to be overcome in achieving semantic interoperability, and the challenge posed by the heterogeneous nature of EHR systems.

Furthermore, the research conducted by Adel, El-Sappagh, Barakat, and Elmogy, (2019) and Lee, Kim, and Lee, (2021), effectively demonstrated the growing significance and adoption of healthcare standards for electronic medical records, the successful navigation of organizational obstacles, and the establishment of interoperability among healthcare providers. In light of the provided backdrop, the study investigated the contemporary implementation of standards and the technological components that would ultimately form the environment for a semantically interoperable Electronic Health Record (EHR).

According to Ministry of Health, (2016), The Kenya eHealth Development Unit is overseen by the Division of Monitoring and Evaluation, Health Research Development, and Informatics. The Division's present interaction with the Ministry of ICT (MoICT) is ineffective, making it unable to assess, monitor, and regulate Kenya's eHealth systems. Furthermore, the ministries do not maintain a centralized register of all eHealth projects in Kenya. To analyze the condition of eHealth in Kenya, this policy development team used a hybrid research technique. Standards for eHealth hardware and software are necessary. Another area that requires standards is the procurement of eHealth solutions to ensure quality, confidentiality, privacy, security, and the integrity of health data.

The eHealth Implementation brings physicians and health informatics experts together to create a single paradigm for integrating eHealth into healthcare systems. The model must be based on existing technologies, infrastructure, health enterprise architecture, data repositories, rules, and standard operating procedures (SOPs) for the smooth adoption, installation, and use of eHealth apps(Ministry of Health, 2016).

### 4.1 Health Interoperability Standards

Integration and information exchange between health organizations and system providers are currently seen as challenges. Each institution often has its own internal ecosystem as well as a proprietary means of storing electronic health data from a patient's history. Recent research looks into the benefits of an integrated ecosystem by exchanging information among inpatient care actors. Many efforts are being undertaken to improve the sustainability of health care, the economy, and process management. Some examples include reducing medical errors, disease control and monitoring, personalized patient care, and avoiding redundant and fragmented data in the electronic medical record. Similarly, some study indicated technologies that could successfully and efficiently achieve this goal, with the ability to interoperate data and allow the analysis and application of health information. Semantic interoperability attempts to share data across all organizational sectors, including clinicians, nurses, labs, and the entire hospital, to achieve this goal. To send data across corporate boundaries, avoid data silos, and retain data independent of vendors(Mello, et al., 2022).

PFT technology is not yet mandated to be interoperable with other clinical data systems, including electronic health records (EHRs), according to a workshop titled "Electronic Health Records and Pulmonary Function Data: Developing an Interoperability Roadmap" at the American Thoracic Society 2019 International Conference. For this workshop, they gathered a diverse group of experts and stakeholders from patient advocacy organizations, adult and pediatric general and pulmonary medicine, informatics, government and healthcare organizations, pulmonary function laboratories, and EHR and PFT equipment and software companies. The participants were charged with two main goals: identifying the major constraints to PFT system and EHR interoperability and proposing remedies to those limitations. PFT data interoperability with the EHR has far-reaching implications for individual patient health and clinical care, community health, and research. Existing EHR-PFT device systems lack sufficient data standardization to enable interoperability. The expense of PFT-EHR compatibility is a significant hurdle, and incentives are insufficient to justify the required investment. The current vendor-EHR system is rigid, prohibiting interoperability(McCormack, et al., 2021).

According to Min, Tian, Lu, An, & Duan,(Min, Tian, Lu, An, & Duan, 2018), The purpose of a clinical data registry is to improve the quality and safety of care for a patient group by collecting and maintaining data about procedures and results. Semantic interoperability is hindered by the difficulty of integrating data from several clinical data registries. The openEHR method employs multi-level modeling to convey the information and knowledge semantics, and it advocates collaborative modeling to facilitate the re-use of existing archetypes with consistent semantics.

The integration of medical data into big data analytics relies on the development of health data standards. These norms establish a common vocabulary and structure for the representation, interchange, and use of healthcare data

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across a wide variety of systems and institutions, allowing for deeper and more accurate analysis.

Some examples of common health data standards include Health Level Seven (HL7) and DICOM (Digital Imaging and Communications in Medicine), as well as ICD (International Classification of Diseases), SNOMED CT (Systematized Nomenclature of Medicine, Clinical Terms), and LOINC (Logical Observation Identifiers Names and Codes). Clinical documentation, imaging, laboratory analysis, and diagnosis are only few of the many aspects of healthcare that are covered by these rules.

Several different health data standards have been created for widespread implementation. The International Classification of Diseases (ICD), the Systematized Nomenclature of Medicine (SNOMED) Clinical Terms (CT), and the Logical Observation Identifiers Names and Codes (LOINC) are all examples of such coding systems. No universally accepted EHR standard has been identified. The retrieved information adheres to a number of different standards, including OpenEHR, ISO 13606, and HL7. Electronic health records do not adhere to a single standardized format, as was previously acknowledged. There are advantages and disadvantages to using any given standard.

Electronic health records, imaging systems, and clinical trials are just a few examples of where several sources of medical data will need to employ standardized formats and vocabularies in order for the data to be successfully integrated. This standardization enables the data to be communicated and evaluated reliably across different systems, which helps to reduce the likelihood of mistakes, inconsistencies, and misinterpretations.

In addition to streamlining the transmission and processing of health data, data standards also facilitate communication between different systems and technologies. By facilitating the transfer of healthcare data across different systems using modern web technologies, such RESTful APIs, the FHIR (Fast Healthcare Interoperability Resources) standard simplifies the incorporation of healthcare data into big data analytics. Electronic health records do not have a universally accepted standard. Multilayer standards such as OpenEHR, ISO 13,606, and HL7 formats can be seen in the extracted data; nevertheless, a dual model approach allows for collaboration between technology and health specialists.

Table 2 shows that the majority of the research centered on how to select standards for a semantic dataset to enable semantic interoperability.

**Table 2 : Standards for Health Interoperability Employed in Selected Studies**

| Health Interoperability standards | References |
|---|---|
| HL7 CDA (Clinical Document Architecture) | (Yuksel, et al., 2016) |
| HL7 CDD (Continuity of Care Document) | (Bahga & Madisetti, 2013),(Yuksel, et al., 2016) |
| HL7 HQMF (Health Quality Measure Format) | (Yuksel, et al., 2016) |
| ISO 13606 | (Carmen, Martínez, Menárguez, & Fernández, 2016) |
| OpenEHR | (Carmen, Martínez, Menárguez, & Fernández, 2016) |
| FHIR (Fast Health Interoperability Resources) | (Ayaz, Pasha, Alzahrani, Budiarto, & Stiawan, 2021), |

According to the research findings, there is a tendency toward two-level open health standards, notably openEHR and ISO 13606. In addition to exchanging data and addressing semantic interoperability difficulties, such as in Moreira, et al., (2018), the authors developed a framework to predict high-risk pregnancy scenarios utilizing ontology resources. The essay also featured an overview study of three open standards, openEHR, ISO 13606, and HL7 CDA, outlining their advantages and disadvantages. Maldonado, et al.,(2020), Carmen, et al.,(2016), search for solutions to merge openEHR and ISO 13606, two open standards with similar specifications. This common approximation method would allow for data standardization. Despite the fact that both standards employ the Architectural Description Language (ADL), there are certain

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differences in the types and definitions that must be resolved.

Taweel, et al. (2011) and Yuksel, et al. (2016) investigated options that differed somewhat from the known goal of standards. Unlike the traditional search platform Clinical Knowledge Manager, Yang, Huang, & Li (2019) provided a methodology to represent the dependencies between data items, concepts, and archetypes on a three-level Bayesian network and used the inference process to uncover relevant archetypes. On the other hand, the authors of Yuksel, et al., (2016) improved the post-sale drug tracking system that is now available to patients. The figures are based on voluntarily filed reports (spontaneous reporting, but only on negative instances). The adoption of an EHR would allow for the tracking of a patient's whole medical history as well as the prediction of important risk factors.

The writers of Bahga & Madisetti(2013) investigated into another possibility. They proposed changes to ISO 11179 and developed a federated Metadata Registry/Repository (MDR), a data metadata database that includes Common Data Elements (CDE) and HL7 CCD (Continuity of Care Document) models. It was also incorporated as a service-based component in the Health Level 7 (HL7) Virtual Medical Record (vMR) (Marcos, González-Ferrer, Peleg, & Cavero, 2015), which proposes to gather patient data from various databases to enable the use of EHR data for clinical decision support.

Three applicable standards based on Detailed Clinical Modeling methodologies have been reviewed for their design, modeling capabilities, flexibility, and resources: OpenEHR, ISO 13606, and HL7 FHIR. The research yielded the following conclusions: the three standards are useful for the reasons for which they were designed and show shortcomings in those for which they were not. They are also functionally compatible in health data platforms and methodologies developed from a standards-agnostic perspective, as well as semantically and technically compatible, implying that choosing one over the other has no significant impact as long as one begins with the one richer in modeling.

### 4.2 Terminologies, Classification and Health Repositories

Terminologies and vocabularies are vast sets of terms for a subject field that give language its commonality. Terminologies provide formal classifications like diseases, occurrences, processes, and specimens to prevent local terms, new words, and human typing from entering the EHR. When sensitive information is shared throughout healthcare facilities, systems must communicate it without losing the intended meaning. One alternative is to create a local repository and govern a configuration that employs proprietary notions. However, because of the acceptability of international vocabulary, using broad phrases and other categories will always mean the same thing to any recipient. Table 3 lists the most commonly used terms in research.

**Table 3 : The international terminologies and classifications**

| | |
|---|---|
| ICD-9, ICD-10, ICD-11 (International Classification of Diseases-version 9, ICD-10 and 11) | (Yuksel, et al., 2016), (Moreira, Rodrigues, Sangaiah, Al-Muhtadi, & Korotaev, 2018) |
| SNOMED-CT (SNOMED Clinical Terms) | (Carmen, Martínez, Menárguez, & Fernández, 2016)(Yuksel, et al., 2016) |
| LOINC (Logical Observation Identifiers Names and Codes) | (Legaz-García, Menárguez-Tortosa, Fernández-Breis, Chute, & Tao, 2015) |
| MeSH (Medical Subject Headings) | (Carmen, Martínez, Menárguez, & Fernández, 2016) |
| MedDRA (Medical Dictionary for Regulatory Activities) | (Yuksel, et al., 2016) |
| WHO-ATC (World Health Organization Anatomical Therapeutic Chemical) | (Yuksel, et al., 2016) |

Several standards, including the RadLex, the Systematized Nomenclature of Medicine-Clinical Terms (SNOMED CT), the Logical Observation Identifiers Names and Codes (LOINC), and the International Classification of Diseases-10-Clinical Modification (ICD-10-CM), are described in terms of their primary characteristics as lexicons, coding systems, or ontologies. The use of standardized clinical terminology, coding, and ontologies aids in communication and efficiency (Wang, 2018).

Since health standards are databases that can be searched, browsed, and updated, they are able to conform to a number of different vocabularies. SNOMED CT is an initiative to improve communication between healthcare and research institutions. SNOMED CT is widely used because it provides a standardized, clinically-validated vocabulary. Thus, articulation can develop to accommodate changing needs (SNOMED International, 2021). The majority of studies concentrated on acquiring the comparison, as discovered when they compared SNOMED CT to disease classifications in the realm of diagnostic and problem list. Research from a variety of countries shows that SNOMED CT was implemented in some form during the adoption process, albeit this may have been done using varying evaluation methods depending on the country's level of SNOMED CT implementation.

According to Millar, (2016), SNOMED CT is the most extensive and multilingual clinical healthcare terminology in the world. In addition, he promotes SNOMED CT as a reliable repository of authoritative clinical content. By using SNOMED CT, clinical content in EHRs can be represented in a way that is both consistent and machine-process able. As an integral aspect of creating electronic health records, SNOMED CT can be utilized in software to consistently, reliably, and comprehensively describe clinically meaningful information. The development of comprehensive, high-quality clinical content for use in medical records is aided by SNOMED CT. It enables computerized interpretation of the healthcare professional's recorded clinical jargon. Clinical validation has been performed on the controlled vocabulary known as SNOMED CT. It has a wide range of possible interpretations, and its expressive capacity can grow with time to meet emerging needs. Clinical information based on SNOMED CT is beneficial to people, professionals, and populations because it supports evidence-based care. Electronic health records (EHRs) improve coordination of care by increasing accessibility to critical information. IHTSDO works with other organizations to establish common standards for the sake of interoperability. Working with ICN to promote the use of ICNP and SNOMED CT has been a key part of the collaboration.

Since ICD-11 and ICHI may only be used in extremely narrow contexts to annotate procedures and diagnoses, SNOMED CT fills in the gaps left by ICHI and ICD-10. It is widely acknowledged in the literature that accurate mappings from ICD-11 to SNOMED CT are challenging. SNOMED CT's potential in eHealth applications might be seen as more favorable than ICD-11 or ICHI in terms of content expressivity and worldwide usability, although taking into account the initial scope of these categories, illnesses, and procedures. For some applications, it's possible that ICHI will be recommended.

In order for institutions to reliably and mechanically share data, electronic medical records must have standard clinical coding systems like SNOMED-CT, LOINC, and ICD-9 CM. However, there is no universally accepted coding system that records all pertinent clinical data for use in patient care, scientific investigation, and reporting on the health of a population.

Interoperability in electronic health records (EHR) and effective information flow across different providers requires standards; nevertheless, the next stage requires knowledge sharing and the inclusion of semantic value. Sharing a common vocabulary facilitates the drawing of conclusions from data and the discovery of unexpected relationships within existing datasets. The primary difficulty of semantic modeling is in the necessity of associating words and phrases with their meanings.

### 4.3 Approaches Proposed to Achieve Semantic Interoperability

The selected research showed that standardization is helpful toward the goal of semantic interoperability. They looked at cutting-edge approaches to integrating health and technology standards for the purpose of reaping the benefits of standardization more effectively. Similarly, additional studies implement semantic web technologies to fulfill data harmonization and extraction needs.

As reported by Mello et al. (2022), Integration and information exchange among health organizations and system providers have been shown to be challenging. Each business has its own unique environment and system for storing electronic health records of past patients. The advantages of sharing patient data between different hospitals have recently been studied. Health care, the economy, and the long-term viability of process management are all areas where efforts are being made to improve. Some features of the electronic medical record include the reduction of medical errors, the control and monitoring of diseases, the personalization of patient care, and the elimination of redundant and disconnected data. Similarly, studies have shown that certain technologies can accomplish this goal effectively and efficiently, allowing for the sharing of data and the interpretation and application of health records. Therefore, semantic interoperability seeks to facilitate information exchange between all hospital departments, including clinicians, nurses, and the laboratory. Therefore, it's important to retain data regardless of vendors and prevent data silos if you want to share information across departments. The need for solutions to the challenge of sharing old and heterogeneous data between healthcare institutions follows logically.

according to Carmen, et al.,(2016) and Yuksel, et al., (2016), health interoperability standards that allow semantic interoperability are typically chosen by electronic health record systems. Implementing semantic interoperability offers the added benefit of enhancing data quality. These works are also directly related to the usage of clinical model representations. Urov, et al., (2012), also presented an agent-based approach to organize the IHE community, whereas Carmen, et al.,(2016), introduced OWL semantic structures, where they also operate as semantic mediators (Bahga & Madisetti, 2013). Hundreds of biological ontologies are accessible in OWL format in the BioPortal repository, which has supported the use of ontologies in various studies to convert clinical models, data, and other terminologies to this natural representation format. The authors of Carmen, et al.,(2016) , researching data semantic representation in ontologies is appropriate since ontological systems allow reasoning to generate alternative meanings and other structures often have clear data relationships. For these reasons, representing EHR metadata in ontologies appears to be a good alternative for semantic goals. Furthermore, the use of ontologies for mapping rule data access scenarios has piqued the interest of researchers.

Several research, including Menárguez-Tortosa, Martnez-Costa, and Fernández-Breis (2012), and Fernández-Breis, et al., ((2013) propose the creation of automated interfaces utilizing archetypes derived from the openEHR and ISO13606 standards. Several studies have also examined the manner in which different reference models (RM) of the openEHR and ISO136060 standards represent archetypes, rules, and relationships. The authors of Ellouze, Bouaziz, and Ghorbel (2016) and Lozano-Rub, Carrero, Balazote, and Pastor (2016), and Lozano-Rub, Carrero, Balazote, and Pastor (2016)) have developed an OWL ontology to represent the reference model and archetype constraints. This ontology describes instances and facilitates the maintenance of a single instance of information by eliminating duplicate cases. This approach ensures a consistent relationship between the reference model and archetype. According to Ellouze, Bouaziz, and Ghorbel (2016) the quality of the utilized archetypes plays a crucial role in determining the extent of semantic interoperability achievable among electronic medical record (EMR) systems. Hence, the integration of the semantic component is crucial when undertaking the task of building archetypes.

To achieve semantic interoperability among archetypes-based electronic medical record (EMR) systems, it is necessary to construct an ontological source and annotate archetypes. Min, Tian, Lu, An, and Duan (2018), conducted a study within the CCTA registry, wherein they incorporated a total of 183 data pieces encompassing 20 archetypes. There was a semantic overlap observed between a combined total of 45 data components from both the Coronary Computed Tomography Angiography (CCTA) and Electronic Health Record (EHR) datasets. Out of the total, it was observed that 38 CCTA data items, accounting for 84%, were included in the 10 repeated EHR archetypes. The clinical data that were collected for this study were obtained straight from the electronic health record (EHR) system without undergoing any type of alteration. The remaining seven data components from the CCTA, accounting for 16% of the total, were acquired through the application of mapping rules and can be considered as a single, more generalized data element within the Electronic Health Record (EHR) system. The results indicated that the methodology employed had the potential to improve the semantic interoperability of clinical data registries. The researchers reached the determination that the implementation of a clinical data registry using an openEHR-based approach has the potential to improve semantic interoperability. Several obstacles related to achieving broader semantic interoperability were identified, including the participation of domain experts, the sharing and reuse of archetypes, and the mapping of archetypal semantics. Possible resolutions to these issues encompass the establishment of semantic associations, cooperative modeling, and the implementation of user-centric technologies.

A recent study has unveiled a correlation between the integration of semantic web technologies and health standards, resulting in the attainment of semantic interoperability. The acceptance of OWL and RDF ontologies for representing reference models and archetypes lacks unanimity, despite their usage in this domain. Costa, Tortosa, and Breis (2010), have provided evidence for the notion that Archetype Definition Language (ADL) frequently represents archetypes and possesses a greater emphasis on syntax. Consequently, it is found to have limitations in attaining semantic interoperability, thereby warranting the integration of ontologies and clinical models.

While certain criteria can be assessed, the selected studies did not provide conclusive evidence about the impact of health standards on database selection. An example of this may be seen in the inclusion of the Virtuoso multi-model bank in HL7 and openEHR systems, where no explicit reference is made to its reliance on a specific standard type. In the presence of ontologies, the utilization of a graph database enables the querying of ontologies, hence facilitating the possibility of a hybrid solution in conjunction with semantic web technologies. In contrast, the authors Mello et al. (2022), introduced a conceptual framework that facilitates the storage of archetypes and enables querying using Archetype Definition Language (ADL). The utilization of ISO 13606 and openEHR standards is contingent upon the user's individual preferences. There is a limited body of research that has specifically examined the type of database utilized by various solutions. Additionally, the other storage structures investigated in these studies did not exhibit a significant correlation or reliance on health standards.

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### 4.4 Security and Integrity of Shared Medical Data

One of the challenges associated with data sharing pertains to security concerns, including the utilization of anonymous data and the implementation of identifying elimination measures. Furthermore, it is imperative to incorporate secure protocols in all forms of communication with diverse entities, even those encompassing proprietary technologies. One of the primary problems pertains to the maintenance of security and integrity in a manner that does not compromise the quality of patient data.

Transparency is a fundamental element of interoperability, which is realized by upholding personal data privacy in accordance with relevant regulatory frameworks for the exchange and confidentiality of health information (Health Act, 2017)(Data Privacy Act, 2019). The successful execution of this task necessitates the incorporation of suitable technical safeguards that adhere to established standards. These safeguards may include the utilization of encryption techniques for databases and files, as well as the application of pseudonymization and anonymization methods to protect potentially identifiable data fields inside datasets containing sensitive medical and personal information (Ministry of Health, 2020).

It is imperative to ensure the security of any health information that includes an identifier linking it to a particular patient. Illustrations of such identifiers encompass personal name, social security number, telephone number, email address, residential address, and additional pertinent details. The Health Insurance Portability and Accountability Act (HIPAA) aims to impose penalties on individuals who breach confidentiality regulations and limit the disclosure of protected health information to authorized personnel with a legitimate purpose. The Health Insurance Portability and Accountability Act (HIPAA) provides protection for individuals and organizations involved in the handling of healthcare data, including electronic medical records and the transmission of medical information within and outside of healthcare facilities (Edemekong, Annamaraju, & Haydel, 2022).

According to Kayaalp (2018) study, the Privacy Rule of the Health Insurance Portability and Accountability Act (HIPAA) offers a legislative framework that balances security measures and the accessibility of health information for secondary purposes. The regulation delineates the specific conditions in which health information is afforded legal protection, as well as the protocols for rendering protected health information devoid of personal identifiers for subsequent utilization. The advancements in artificial intelligence and computational linguistics have led to the creation of computational text de-identification algorithms. These algorithms have demonstrated the ability to deliver de-identified findings that are comparable to those generated by human professionals. Moreover, they offer significant advantages in terms of speed, consistency, and cost-effectiveness. The author also provides an in-depth analysis of the current advancements in clinical text de-identification systems, highlighting their role in facilitating the utilization of de-identified clinical data for big data purposes. Moreover, the author strongly advocates for the protection of patient privacy throughout this process. The author additionally noted that the process of de-identifying clinical text is not flawless. It is imperative for all parties involved, such as patients, healthcare organizations, institutional review boards, scientists, scientific communities, regulatory bodies, and law enforcement agencies, to work together closely. This collaboration is necessary to ensure the utmost protection of patient privacy and to liberate clinical and scientific information from the limitations imposed by electronic healthcare systems. Regulations pertaining to public health and privacy serve to define norms and restrictions, including limitations on the solicitation and dissemination of health-related data solely to the extent necessary for a particular scientific investigation. The instructions provided by developers of de-identification systems aim to optimize the functionality and efficacy of their devices, hence increasing the likelihood of successful de-identification outcomes. In order to effectively ensure patient privacy, organizations with clinical repositories must rigorously adhere to these legislation and norms. Healthcare institutions require cooperation from the public, scientific communities, as well as local, state, and federal politicians and government agencies to facilitate their de-identification and data sharing endeavors. This collaborative effort is crucial for enabling scientific communities to access and utilize big data resources.

The selected research exhibited a lack of consistent adherence to data privacy rules. The research emphasized the significance of the Health Insurance Portability and Accountability Act (HIPAA) in relation to issues pertaining to security and privacy. The storage and management of health data in the publication by Bahga and Madisetti (2013) incorporated the principles outlined in the Health Insurance Portability and Accountability Act (HIPAA) as well as certain guidelines from ISO 13606 (Moreira, Rodrigues, Sangaiah, Al-Muhtad, & Korotaev, Semantic interoperability and pattern classification for a service-oriented architecture in pregnancy care , 2018). Alternatively, it might be conjectured that the authors want to achieve universality in relation to regional legislation by maintaining a distinct separation between the security requirements and interoperability solutions. Every country possesses its own set of regulations that dictate the utilization, dissemination, and safekeeping of personal data, encompassing identifiable information as well as financial or medical records. This suggests that the investigations prioritize the execution of trials that accurately represent practical requirements, leveraging real-world data, while ensuring that research remains an autonomous decision-making process.

## V. RESULTS

The study focused on evaluating how these existing architectures facilitate or hinder the seamless integration of medical data into Big Data analytics, particularly in terms of semantic interoperability in healthcare domain.

### 5.1 Health Insurance Portability and Accountability Act (HIPAA)

According to the study, HIPAA is critical in promoting patient privacy and fostering confidence between patients and healthcare providers. It promotes the use of electronic health records and interoperable systems, allowing for secure information sharing while retaining anonymity. HIPAA compliance is critical for avoiding legal and financial fines, as well as contributing to the overall integrity of the healthcare system.

However, implementing and complying with HIPAA can be difficult because to the laws' complexity, which requires healthcare businesses to accurately interpret and apply them. This may necessitate large resources, such as trained personnel and technological infrastructure. Furthermore, the ever-changing technology world and data security threats represent continual problems, needing continuous changes to security measures and remaining up to speed on best practices to protect patient data.

By offering defined data models, encouraging uniform representation of clinical concepts, and facilitating clear information transmission, OpenEHR, ISO 13606, and HL7 all support semantic interoperability of integrating medical data into a big data analytics environment. Healthcare organization may make sure that their data is semantically compatible by following these standards during data integration. This will enable more meaningful analytics, research, and decision-making in a big data analytics context.

### 5.2 OpenEHR

According to the study, the archetyping method used by OpenEHR plays a crucial role in achieving semantic interoperability. OpenEHR ensures that medical data is consistently represented, regardless of the source system or application, by employing standardized, domain-specific models called archetypes for clinical concepts. These archetypes capture the complex semantics of clinical data, enabling a comprehensive and accurate representation of medical information.

The study suggests that following the OpenEHR archetypes when integrating medical data into a big data analytics environment is highly beneficial. It ensures that the data maintains its context and meaning, promoting semantic consistency and interoperability across diverse data sources. By adhering to these archetypes, healthcare organizations can enhance the quality and reliability of integrated data, leading to better insights and outcomes in big data analytics.

The findings highlight the significance of the OpenEHR archetyping method in achieving semantic interoperability and emphasize the importance of utilizing archetypes for integrating medical data into big data analytics environments. Doing so guarantees consistency and meaning in the data, enhancing its usefulness and enabling seamless data exchange and analysis across different healthcare systems and applications.

### 5.3 ISO 13606

While ISO 13606 has been discontinued and succeeded by other standards such as ISO 13940 and ISO 13941, its influence on semantic interoperability remains relevant. ISO 13606's two-level modeling approach, with a generic reference model and domain-specific models, helps ensure that medical data can be shared and understood consistently across different healthcare systems. When integrating medical data into big data analytics, using ISO 13606-compliant models for data exchange fosters semantic alignment, making it easier to combine and analyze data from various sources.

### 5.4 Health Level Seven (HL 7)

The study discovered that HL7 enables smooth integration by standardizing healthcare data representation and assuring system compatibility in sections 2.6.1 and 2.6.3. It lets various healthcare systems, such as EHRs, laboratory systems, and imaging systems, to share data in a standardized manner, facilitating the smooth integration of medical data from different sources into Big Data analytics. Data can also be translated from proprietary formats into a standardized HL7 format, simplifying data integration and improving data quality.

However, the study highlighted significant impediments to seamless integration. One problem is the existence of multiple versions of HL7, which makes integrating medical data from systems that use different versions challenging. Concerns about system compatibility can stymie the inclusion of data into Big Data analytics tools.

Furthermore, HL7 was found to lack semantic interoperability, which is critical for understanding the meaning and context of data in complex Big Data analytics, potentially limiting research depth and insights. In addition, HL7 primarily focuses on clinical and administrative data, and it may not cover other data domains such as socioeconomic determinants of health or genomic data, making the integration of diverse data forms difficult.

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### 5.5 Fast Healthcare Interoperability Resources (FHIR)

FHIR is a healthcare interoperability standard developed by HL7 that provides various benefits for data modeling, representation, and interchange in Big Data analytics. FHIR's resource-based approach allows for flexible data modeling, making it ideal for a wide range of healthcare use cases and data formats. It also separates healthcare data into distinct resources, allowing for selective data retrieval and efficient data interchange in Big Data analytics.

The study also discovered that FHIR makes use of RESTful APIs, which are extensively utilized in modern web development, making integration into apps and systems easier and data interchange with Big Data analytics platforms easier. FHIR contains privacy and security issues as major components, ensuring secure data sharing and management throughout the healthcare data exchange lifecycle, in addition to data representation and interoperability.

To enhance semantic interoperability, it was found out that FHIR combines standardized terminologies like SNOMED CT and LOINC, leading to more accurate and meaningful data exchange in Big Data analytics.

Despite the continuing adoption of FHIR-based systems and applications, the study suggests that certain healthcare organizations continue to rely on older systems that may not support FHIR natively, posing issues when dealing with Big Data analytics tools. While FHIR provides defined nomenclature, true semantic interoperability remains a concern, potentially compromising data integration and analysis quality and consistency.

FHIR adoption, on the other hand, creates an interoperability ecosystem, with the expansion of FHIR-based apps, tools, and frameworks promoting innovation and improvement in healthcare analytic.

In contrast to the HL7 standards, which have an ecosystem of standards but all might not have the same objective, it was found that the dual model of openEHR and ISO 13606 can be shared to improve interoperability architecture. The HL7 organization also has an extensive list of terminologies that are compatible with the standards that are currently in use. In addition, it was found out that EHR advocates the opposite yet HL7 standard prioritizes on a cordial relationship with the developer, technical documentation and structures similar to the development ecosystem. This implies that the choice of health standard may be related to some implementation team characteristics.

Key functions, similarities, differences, benefits, and drawbacks of the different health standards discussed in the findings above are depicted in Table 4.

Table 4: Health standards architectural frameworks

| Health standards architectural frameworks | Key Functions | Similarities | Differences | Benefits | Drawbacks | Impacts |
|---|---|---|---|---|---|---|
| HIPAA | - Promotes privacy and security of patient data | - Encourages adoption of electronic health records | - Compliance with regulations is essential to avoid penalties | - Builds trust between patients and healthcare providers<br>- Facilitates data sharing among healthcare providers | - Complexity of regulations may require significant resources<br>- Continuous updates for data security | - Enhances patient confidentiality and data security<br>- Fosters trust and confidence in healthcare systems |
| OpenEHR | - Supports semantic interoperability | - Ensures consistent representation of medical data | - Requires data mapping and integration efforts | - Provides standardized domain-specific models - Improves clinical documentation accuracy and specificity | - Implementation challenges may arise in integrating with existing systems | - Enables seamless data exchange between different healthcare systems<br>- Enhances data consistency and quality |
| ISO 13606 | - Facilitates clear information transmission | - Provides standardized nomenclature for laboratory and clinical observations | - May lack comprehensive coverage for novel laboratory tests or clinical results | - Enables uniform representation and comprehension of medical data<br>- Promotes data interoperability | - Requires regular updates to include new clinical data<br>- Implementation may be time-consuming | - Enhances data sharing and communication among healthcare professionals and systems |
| HL7 | - Supports data exchange and interoperability | - Enables communication of clinical and administrative data between healthcare systems | - Some standards within the ecosystem may have different objectives | - Offers an extensive list of compatible terminologies in use<br>- Emphasizes technical documentation and relationships | - Different objectives within the HL7 ecosystem<br>- Complexity in integrating various standards | - Facilitates seamless data exchange between diverse healthcare applications and systems |
| FHIR | - Enables flexible data modeling | - Provides resource-based approach for easy data modeling and representation | - May face challenges in adoption and integration with existing systems | - Allows scalable and modular data exchange - Supports RESTful APIs for integration with modern web development | - Adoption and implementation difficulties<br>- Limited maturity compared to other standards | - Facilitates easy integration of health data into modern web -based applications and analytics tools |

The study suggests that during data integration, adhere to defined data formats and standards such as FHIR, OpenEHR, ISO 13606, and HL7 to assure semantic compatibility and increase the value of medical data in Big Data analytics. However, while selecting the optimal architecture for data integration and analytics, healthcare companies should carefully assess their specific demands and resources.

## VI. CONCLUSION

In conclusion, each health standard serves specific functions and offers unique benefits and drawbacks. They share similarities in promoting interoperability and data exchange but differ in their approaches and objectives. Implementing these standards can have significant impacts on enhancing data quality, communication, and data exchange across healthcare systems, ultimately leading to improved patient care and healthcare outcomes. However, the challenges in adoption and implementation must be carefully considered to ensure successful integration and utilization of these standards in healthcare settings.

The findings of the study will help guide the development and improvement of architectures for integrating medical data into Big Data analytics, ultimately facilitating more effective analysis and insights for healthcare professionals and researchers

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