A Fuzzy Ontological Model for Semantic Interoperability in Distributed Healthcare Information Systems

Joshua Okemwa[1], Dr. Patrick Oduor Owoche[2], Prof. Samuel Mungai Mbuguah[3]

[1]Department of Computing Sciences, Kisii University, Kenya

[2,3]Department of Information Technology, Kibabii University, Kenya

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ABSTRACT

The exchange of patient or care data across heterogeneous health systems is crucial in the modern healthcare ecosystem yet remains daunting. Integration and interoperability in siloed health applications require robust health information exchange (HIE) and a pragmatic ontological model to be successful. This paper details a prototype development endeavor and systematic review of literature that has pioneered the development of a robust, practical, and tested fuzzy ontological model to enhance semantic interoperability in siloed, distributed health systems. Leveraging the tenets, standards, LOINC codes, and developed model from this study will enable robust and flexible data mapping and sharing health data in an environment marred with ambiguities and uncertainties but requiring the sophistry of interoperability.

Keywords: Health Information Systems, Semantic interoperability, Fuzzy ontology, Electronic Health Records, Distributed Systems

INTRODUCTION

The healthcare sector is witnessing a massive uptake of technology to automate patient records management in the provision of care [1]. The growing volume of data in the healthcare sector has been the cornerstone of this digital revolution. With electronic health records (EHRs), electronic medical records (EMRs), and health management information systems (HMISs), healthcare organizations are now able to provide and monitor patient care with greater precision, along with supplementary services such as scouring medical knowledge resources [2]. Extant literature invariably appreciates patient data as an integral constituent of electronic health systems. Correspondingly, authors assert that this data is crucial in streamlining processes and enhancing the delivery of care [3], [4].

Despite this optimistic rendition, in actual practice, these electronic health systems operate in a fragmented and siloed fashion, posing epic challenges in the seamless exchange of data. The absence of unified data structures, schemas, and communication protocols implies that myriad systems must grapple with exchanging data between them seamlessly, if they do at all. Huge capital has been injected into the sector to operationalize interoperability. In the United States alone, for instance, the HITECH Act (2019) - Health Information Technology for Economic and Clinical Health – has seen state agencies invest more than USD 36 billion to empower health information exchange (HIE) networks and promote interoperability [5]. However, data on HIE networks' usage remains low [6], and several barriers thrive as interoperability continues to choke [7].

Semantic interoperability, the sharing of data between heterogeneous systems with unambiguous meaning, leverages HL7, CDA, DICOM, and other similar standards. Nomenclatures such as ICD, LOINC, RxNorm, and SNOMED CT [8], [9]. These standards and nomenclatures make it possible to consistently and uniformly share data, addressing the complex reality of sharing data across different database schemas. Rule-based interoperability has proven little success in advancing the seamless exchange of data in health systems [10]. To address the existing challenges, this paper proposes ontological-based interoperability and a fuzzy ontological model for interoperability. This fuzzy model is set to achieve more robust and flexible data mapping, accommodating the ambiguities and uncertainties present in data presentation and medical terminology.

This paper proposes a fuzzy ontological infrastructure for semantic interoperability in distributed EHR environments to address these challenges. By incorporating fuzzy logic principles, the infrastructure enables more flexible and robust data mapping, accommodating the inherent uncertainties and ambiguities often present in medical terminology and data representation.

Related Work

Past studies have explored different approaches toward achieving interoperability in the health sector.

Standardized terminologies

The use of standardized language throughout the medical field significantly impacts data interoperability. Meaningful use regulations and established standards such as OpenEHR, Fast Healthcare Interoperability Resources (HL7 FHIR), Clinical Data Interchange Standards Consortium (CDISC), SNOMED CT, Continua, Health, Alliance, International Classification of Diseases (ICD), Logical Observation Identifiers Names and Codes (LOINC), Digital Imaging and Communications in Medicine (DICOM), and Integrating the Healthcare Enterprise (IHE) promote seamless data expression and exchange. However, even with these terminologies, improper implementation may result in interoperability issues at various levels.

Ontologies and Models

Literature names various ontology solutions in interoperability, including the Ontology of Enterprise Interoperability [11], the Ontology for Interoperability Assessment [11], Generic Health Concept ontology [12], and Digital Construction Ontologies [13] among others. These and other ontologies are argued to accelerate the implementation of interoperability through availing technology frameworks and robust tools. Further, scholars contend that ontologies can permeate where semantic interoperability alone cannot integrate heterogeneous systems and their databases. Ontologies make it possible to both share data and infer meaning from the shared data [14].

Literature, thus, provides connotations that ontologies can be employed to maximize inferring meaning from coded data, providing granularities of words and coding, providing capacity to cope with temporal change in definitions, fluctuations, and clinical practice, and providing conversion of structural data or records into dynamic ones. Ontologies, just like interoperability, function under standards to maximize interoperable data. Ontology standards common in practice include resource description framework (RDF) [15], SPARQL Protocol and RDF Query Language [16], and OWL web ontology language [17].

Data mapping techniques

Semantic interoperability can draw inferences from data mapping to make data more structurally available. While semantic interoperability focuses on semantics and inferring meaning, structural interoperability narrows down to database schemas. Semantic interoperability, in combination with structural interoperability, alleviates model integration hurdles [18].

Developing and maintaining key terminologies is thus key to semantic interoperability. Terminologies in interoperability might fall into financial, administrative, legal, or clinical categories. Standards regarding terminologies are key to ensuring communication as systems exchange information or for documenting and coding patients' health statuses [19]. Literature suggests that mapping standards include reference and other terminologies (RT). SNOMED CT falls under RT, and many other mappings have been derived from it [20].

METHODOLOGY

A systematic review was conducted to answer pertinent questions about the measurement models for interoperability currently available, the method used to quantify interoperability by these models, and the methodologies and frameworks aligned with interoperability. A scoping review was conducted, and a couple of literature reviews were conducted on modeling semantic interoperability in the health sector. However, different authors provided different views and models, thus invoking a need for harmonization and coming up with a workable model for low-resource settings. These gaps in the current literature confirm the need for a comprehensive, thorough, and updated literature review on modeling semantic interoperability. After conducting the search strategy, 109 primary studies on models of semantic interoperability.

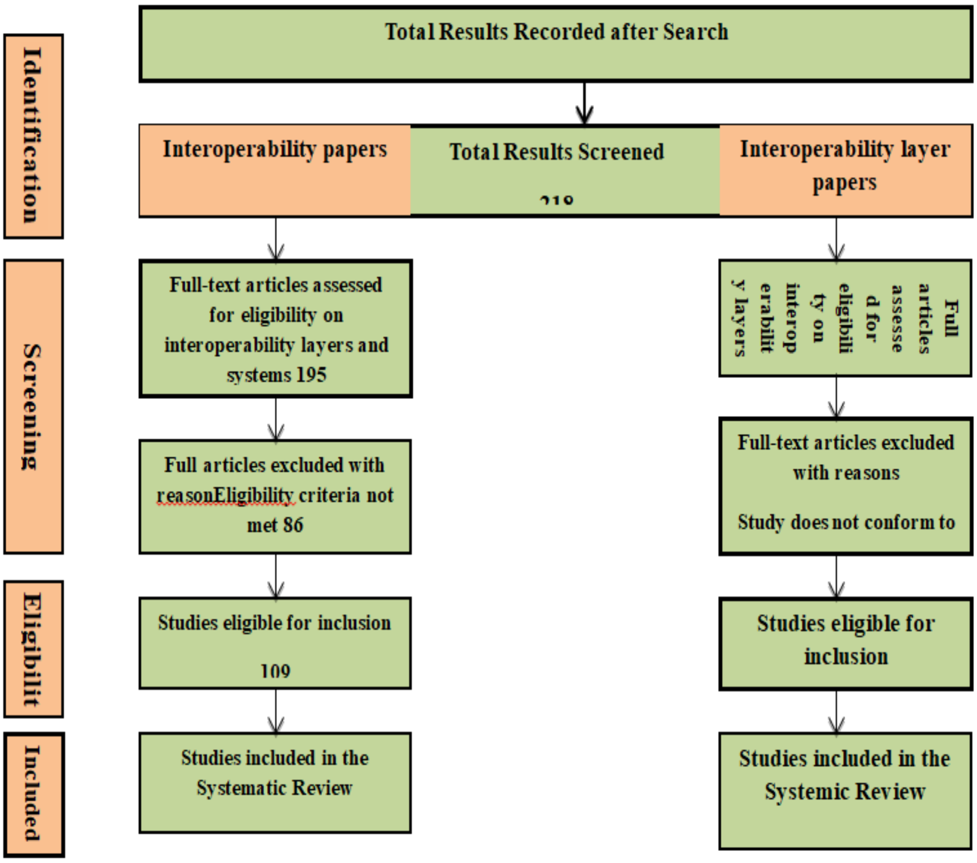

Figure 1: Scoping of literature review

In addition to the literature review, a prototype was developed to simulate the exchange of patient data using SNOMED CT and LOIC terminologies and conversion to XML over two disparate systems. A PHP framework—Larevel version 11—was used to complete the prototype development. The prototype demonstrated semantic interoperability by simulating data exchange across different systems and providing an understanding of its meaning.

```
$obx1 = $xml->addChild('OBX');
$obx1->addChild('SetID', '1');
$obx1->addChild('ValueType', 'ST');
$obx1->addChild('ObservationIdentifier', 'LOINC:8310-5');  // LOINC code for Body Temperature
$obx1->addChild('ObservationValue', htmlspecialchars($vitals->temperature));
$obx1->addChild('Units', 'C');
$obx1->addChild('ReferenceRange', '36-38');
$obx1->addChild('AbnormalFlags', 'N');
$obx1->addChild('ObservationResultStatus', 'F');
```

Code Snippet 1: LOINC terminologies in semantic interoperability and data standardization

A simple XML element was used to handle XML data, and XML files were transferred across the systems through Guzzle HTTP. Guzzle HTTP, available through Laravel, allows sending files to an external API and is documented to allow large uploads. [21].

Proposed Fuzzy Ontological Infrastructure

The proposed framework considers both semantic interoperability and the need for ontologies. Fuzzy ontological infrastructure thus utilizes the widely accepted FHIR's HL7 interoperability standard, SNOMED CT, and LOINC codes to ensure seamless data exchange in health systems.

In implementing interoperability in biomedical research, some authors used a unified ontology that is based on knowledge framework and LexEVS terminology [22]. The approach provides a merger of sorts between semantic and structural interoperability to promote communication in heterogeneous databases [22]. The resultant system is flexible and reduces human interaction when implementing and managing the integration.

The biomedical study instigates the fuzzy ontology for interoperability that aims to be equally flexible in dealing with heterogeneous systems while reducing human interaction. Further, the fuzzy ontology draws from the OWL web ontology language. Specifically, the steps below make the ontology flexible in handling semantic interoperability:

i. Data ingestion – data is collected from electronic devices in EMRs and other sources up to and including IoT devices [23].
ii. Data organization – collected data is organized and standardized to ensure compatibility. At this stage, the fuzzy ontology employs SNOMED – CT and LOIC terminologies to ensure standardization [24], [25].
iii. XML conversion - Implementation of an additional layer of security, SecFHIR, to ensure secure data exchange [26].
iv. Data policies – policy alignment to ensure entities sharing data comply with local and international data protection standards and regulations to meet patient privacy and legal obligations.
v. Machine learning – the use of machine learning to enhance semantic and structural interoperability is a visionary perspective that, when implemented, will integrate data sources with diverse structures and schemas [27].

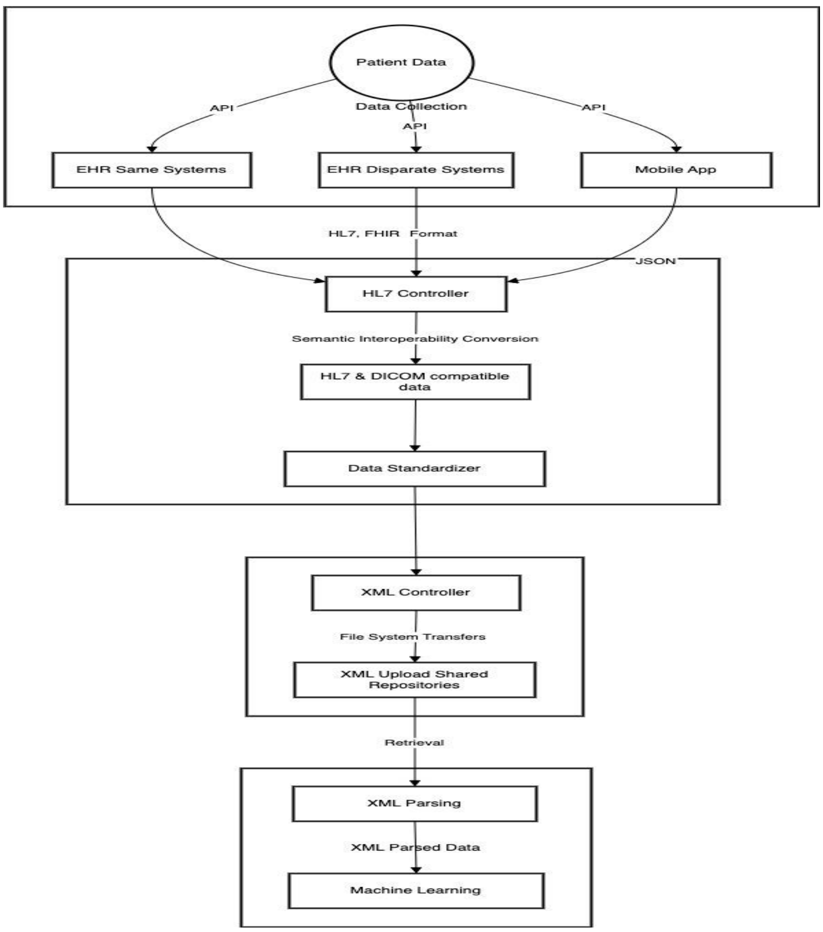

Figure 2: Proposed fuzzy ontological interoperability model

Evaluation

The proposed model adopts HL7 FHIR and utilizes the widely accepted Fast Healthcare Interoperability Resources (FHIR) standard from Health Level Seven International (HL7) to ensure standardized data exchange formats and protocols. The model integrates DICOM, SNOMED-CT, and LOINC standards and terminologies, hence promoting both semantic interoperability and posing ready for structural interoperability.

Implementing a fuzzy ontology means the model can handle uncertainties in data shared from disparate systems, which ensures and enhances semantic matching between heterogeneous data sources.

CONCLUSION

This study underscores the essential role of semantic interoperability in enhancing healthcare delivery, particularly in low-resource settings. While there is a strong acknowledgement of the criticality of seamless data exchange in the healthcare sector, challenges, such as fragmentation, unenforced standards, security concerns, and technical inadequacies, continue to hinder successes. Semantic interoperability on its own may not succeed. However, with the proposed fuzzy ontological model for interoperability, there should be a better exchange of data, and the developed prototype presents this fuzzy (adaptable) model in practice.

Further studies are needed to integrate machine learning (ML) to provide further advancements from semantic and structural interoperability. Additionally, studies are needed to provide performance metrics in comparison to current interoperability models. Lastly, prototypes tested with huge datasets and databases will ascertain the scalability of the proposed model.

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