A Flexible Semantic Integration Framework for Fully-integrated EHR based on FHIR Standard

Ahmed Dridi[1][a], Salma Sassi[1], Richard Chbeir[2] and Sami Faiz[3]

[1] *VPNC Lab., FSJEGJ, University of Jendouba, Jendouba, Tunisia*

[2] *Universite Pau et Pays de l'Adour, E2S/UPPA, LIUPPA, EA3000, Anglet, 64600, France*

[3] *ISAMM, University of Manouba, La Manouba, Tunisia*

{*ahmed.dridi, salma.sassi*}*@fsjegj.rnu.tn, richard.chbeir@univ-pau.fr, sami.faiz@insat.rnu.tn*

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Abstract: Despite the huge efforts focused on EHR development and massive many years of widespread availability of this latter, health care providers and organizations are still looking for innovative solutions to bring in all IoT data, and unstructured data into electronic health record (EHR) systems. There is a growing need to semantically integrate health-related data from different sources to support decision-making and improve the quality of care services provided. In this paper, we propose a flexible semantic integration framework for IoT, unstructured and structured healthcare data in EHR systems called SF4FI-EHR. It is built on a novel approach that applying semantic web technologies and the HL7 FHIR standard to handle integration challenges. Our experiment results from the proof-of-concept study show that the use of such approach does enhance healthcare data integration as well as overcome obstacles that prevent the optimal exploitation of these data.

1 INTRODUCTION

Over the years, a large amount of health-related data is produced, captured and usually accumulated continuously in Electronic Health Records (EHRs) (Menachemi and Collum, 2011). EHR is the most widely used application in the modern healthcare industry, which has been used with the intent to improve quality of care and patient outcomes. With the advent of Internet of Things (IoT) (Ashton et al., 2009), a new research topic in many academic and industrial disciplines, especially in healthcare, has emerged. Wearable medical devices connected to the internet, can help cut costs and improve patient care by collecting invaluable data that give extra insight on the individuals physical condition. These data collected from different sources introduce new challenges related to data integration and processing, due to their structural characteristics, their heterogeneity, and the lack of semantics. It is worthy to note that the main objectives of the IoT-based healthcare systems cannot be achieved without consolidate these data using a well-designed and established methodology so to properly integrate them with others clinical data into the EHR.

[a] https://orcid.org/0000-0001-6374-1883

Despite the massive effort and investment in health information systems to make clinical data interoperable and integrable, the widespread use of the IoT in EHR remains a long-term goal. The need to design appropriate solutions for seamless and effective integration of different health data including IoT and unstructured data into the EHR is more than before.

This paper addresses the problem of health-related data integration, where data from multiple sources needs to be aggregated and integrated in a unified and rich-semantic representation. Healthcare data integration is not a trivial task, but its vital to allow clinicians to get the whole picture of an individuals health related-data. Meanwhile, there are some stark challenges need to be addressed over this task.

The IoT devices continuously generate large amounts of data that can reflect patient's conditions. This data is produced in a mix of data formats, mostly, without a well-defined structure and additional semantic. It has no value in its raw state, so it must be converted into a unified representation, and semantically described to extract high-level knowledge which can be used to make decisions, as well as to make it easy to integrate with other data. IoT data integration in EHR is the first challenge we will focus on in this research.

Another challenge that needs to be addressed is the unstructured health data integration. Roughly 80% of clinical data is unstructured data and still largely untapped after it is created. This data is often recorded as free text, without standard content specifications, that makes it more difficult to be handled by EHR systems. Clinician notes, prescriptions, pathology and radiology reports, and scanned medical documents contains meaningful data to deliver high-value care. Therefore, this useful data needed to be effectively extracted and integrated into the EHR.

In this paper, we are also motivated by enabling semantic interoperability among structured health data. These data are standardized by different standards, encoded with heterogeneous terminologies and stored in various legacy systems and EHRs. For subsequent seamless integration with other data, these data need to be retrieved from their original sources first, and then restructured into a common format and standard terminologies.

Currently, several state of the art solutions, have tried to solve the issue of interoperability and semantic integration of healthcare data. But, to the best of our knowledge, still there is no works are able to perform such integration efficiently, taking into consideration all the challenges aforementioned.

Here, we propose a flexible semantic integration framework, called *SF4FI-EHR*, to capture heterogeneous health-related data from different sources and integrate them into an interoperable integrated EHR.

SF4FI-EHR is based on a set of semantic web technologies and the HL7 FHIR standard (Bender and Sartipi, 2013) to:

- Process non-standardized health related data
- Create structured and machine-readable information and provide means to raw data of various forms
- Seamlessly integrate data to a consistent description format

The rest of the paper is organized as follows. Section 2 introduces main previous work carried-out on health data integration. In Section 3, we present our framework. The subsequent sections detail the main components of the framework architecture. The experimental results are discussed in Section 4. Section 5 describes an example use case to demonstrate the health data integration process by the proposed framework. Finally, Section 6 concludes the paper with suggestions for future work.

2 BACKGROUND AND RELATED WORKS

Semantic interoperability is still one of the primary interests in the E-Health community. In this respect, a lot of efforts have been devoted to achieve semantic interoperability into EHRs. As a result, several EHR standards, terminologies, and semantic frameworks have been proposed in the literature. For instance, many standards organizations have put countless efforts to introduce standards and specifications such as Health Level 7 (HL7) standards, CEN EN 13606, ISO TC 215, and openEHR (Eichelberg et al., 2005). These standards, which are currently in continuous improvement, aim to structure and markup the clinical content for the purpose of exchange (Maharatna and Bonfiglio, 2013). A survey and analysis of EHR standards are presented in (Eichelberg et al., 2005).

Similarly, others attempts (Mori et al., 1998) aims at providing terminological standards and codes , as structured lists of terms that give a controlled vocabulary and structured medically pertinent expressions, covering complex concepts (such as diseases, operations, treatments and medicines). Despite the significant role played by the proposed standards and terminologies in achieving semantic interoperability into EHR, there is still no common consensus regarding their adoption.

Consequently, semantic technologies-based integration frameworks and mediation approaches are required to deal with multiple health data representations. To improve the interoperability of EHRs data, represented with different standards, Sun et al. (Sun et al., 2015) proposed an approach to integrate data from heterogeneous resources. RDF data mapping approach with semantic conversions between different representations has been applied to integrate health records from heterogeneous resources and to generate integrated data in different data formats/semantics to support various clinical research applications. In (Martínez-Costa et al., 2014), Martnez-Costa et al. described a layered semantic-driven architecture to improve EHR semantic interoperability based on ontologies that formalize the meaning of clinical data. Similarly, a semantic-driven engine called SeDIE, which built on a novel approach using a statistical method and a Multiple-Criteria Decision-Making model to overcome the barriers of integrating unstructured and structured data, is described in (Dhayne et al., 2018). A scalable and standards-based framework for integrating structured and unstructured EHR data centered on a clinical NLP pipeline enhanced with an FHIR-based type system, is described in (Hong et al., 2018). Ozgur Kilic et al. (Kilic and Dogac, 2009) proposed mapping clinical statements between EHRs, that resolve integration issues by using archetypes, refined message information model (R-MIM) derivations, and semantic tools.

The issue of EHR interoperability is also addressed by numerous international projects including; the European project EHR4CR (De Moor et al., 2015), eMERGE (Rasmussen-Torvik et al., 2014), SHRINE (Weber et al., 2009), PONTE (Tagaris et al., 2012), EURECA (Genitsaridi et al., 2015), CDISC SHARE (El Fadly et al., 2007), and GALEN (Mori and Consorti, 1998), where authors overcame the interoperability challenges using a platform capable to bring up semantic interoperability services based on standard terminologies.

More recently, increasing interests have been focusing on the integration of the IoT data into EHRs. As a result, much work has been carried out in order to achieving the interoperability of the sensed and EHR data. Kumar et al. (Kumar et al., 2016) successfully integrated patient glucose data in the EHR through an Apple HealthKit, which collects data via Bluetooth, stores them locally on the mobile device and then sends the data to the EHR system through the Epic MyChart app running on the Apples mobile operating system (iOS). In a similar way to Apple HealthKit, V. Gay and P. Leijdekkers (Gay and Leijdekkers, 2015) developed with third-party partners a health and fitness Android application called myFitnessCompanion, which integrates a wide range of wearable devices, EHR systems, and other applications. Vuppalapati et al. (Vuppalapati et al., 2016) reviewed the role of big data and data analytics in healthcare. They proposed a sensor integration framework to integrate various sensors data with the electronic health records. Spark and Apache Kafka are used for processing a large amount of data in realtime. To achieve an effective health self-management, the authors in (Peng and Goswami, 2019) presented an OWL ontology-based approach aiming to integrate the health and home environment data from heterogeneously built services and devices. Links with external ontologies (such as SSN (Compton et al., 2012) and FOA[1]), semantic annotation tools and ontology mapping techniques are used to ensure efficient data integration. Alamri A. (Alamri, 2018) described a semantic middleware that exploits ontology to support the semantic integration of IoT and EHR data. Semantic Web technologies and clinical terminologies are used to dene and normalize the structures and relationships of the data collected from the IoT healthcare devices and sensors and data obtained from EHRs. A clinical decision support system (CDSS) for diabetes self-management is discussed in (El-Sappagh et al., 2019). The proposed CDSS is based on the OWL FASTO ontology [2], which integrates the semantic capabilities of the SSN (Compton et al., 2012), BFO (Grenon et al., 2004), FHIR (Bender and Sartipi, 2013), clinical practice guideline (CPG), and medical terminologies in a unified manner, in order to provide an interoperable integration of IoT and EHR data.

3 *SF4FI-EHR*: SEMANTIC FRAMEWORK FOR FULLY INTEGRATED EHR

Ideally, EHRs must capture and integrate data on all aspects of healthcare over time, with the data being represented according to relevant controlled vocabularies and standards, enabling consequently a different level of interoperability for the purpose of exchange and potential secondary uses.

From this perspective, we present in this paper a flexible semantic framework, called *SF4FI-EHR* standing for Semantic Framework for Fully-Integrated HER, that systematically enables the aggregation of heterogeneous health-related data from different sources and integrates them as an interoperable integrated EHR. *SF4FI-EHR* intends to integrate 3 categories of health-related data: 1) IoT and medical devices generated data, 2) Unstructured, and 3) Structured EHR data. The overall architecture of the proposed framework is depicted in Fig.1.

To deal with the different data categories, a particular integration process is expected for each one. IoT raw-data must be preprocessed, modeled, and then semantically annotated by a modular ontology built by reusing existing knowledge resources. For unstructured EHR data, an advanced Natural Language Processing (NLP) technique is required to identify actionable insights and generate structured output. For this purpose, we chose to use *MetaMap* tool. The structured EHR data are needed to be retrieved from their heterogeneous sources and then converted into a FHIR resources. All collected, preprocessed and standardized data are converted to FHIR resource formats, before being mapped to the FHIR OWL Ontology to construct a comprehensive patient health profile.

As a result, an integrated FHIR-based EHR is created and stored within a Relational DataBase for future purposes. We chose to use RDB since it is more popular and more stable, and most of the current EHR databases are in RDB format.

[1] http://www.foaf-project.org/

[2] https://bioportal.bioontology.org/ontologies/FASTO

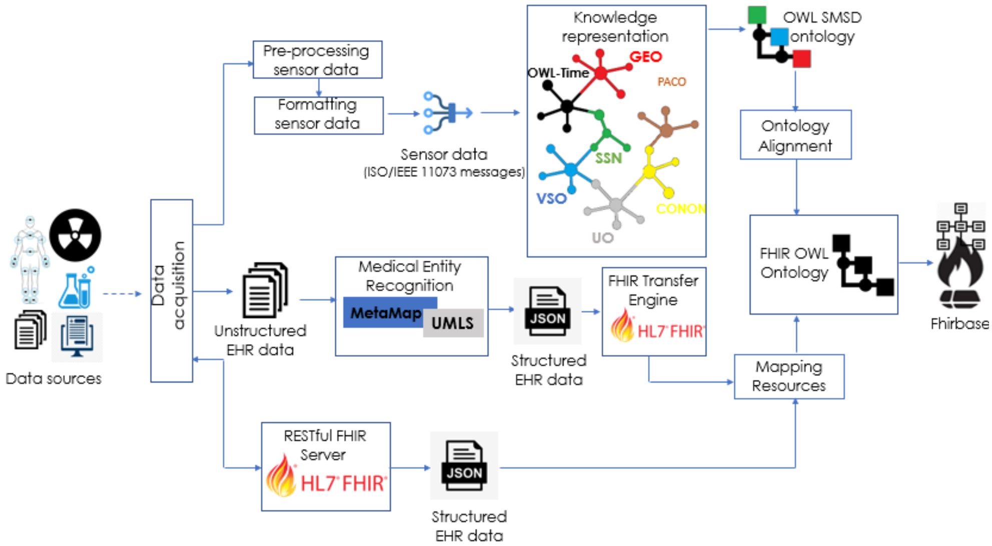

Figure 1: The architecture of the SF4FI-EHR framework.

The next subsections describe in detail the key features of the integration process within the proposed framework.

3.1 IoT Data Integration

IoT medical devices capable of generating data that can be integrated into EHRs to make a significant clinical impact and improve the way the patient is treated by his doctor.

The problem is that IoT raw data streams, sensed in real time, have no structure and semantics, which makes their integration with EHR data challenging. Thus, IoT data must undergo a preprocessing step in order to: fill in missing values, smooth noisy data and delete irrelevant values. Afterwards, these data are converted into a unified format by applying ISO/IEEE 11073-104zz device specifications.

In order to use these sensor data effectively, semantic annotation is applied using a modular ontology that we called Semantic Medical Sensor Data ontology (SMSD). This ontology enables sensor data to be described with semantic metadata in order to make them machine-understandable, interoperable, as well as to facilitate data integration. In order to ensure high reusability, the SMSD ontology was built by extending multiple relevant ontologies. Semantic Sensor Network ontology (SSN) (Compton et al., 2012) has been extented in *SMSD* to cope with sensors networks and data. Furthermore, We extend several concepts from the FOAF ontology[3], VSO ontology (Goldfain et al., 2011), CONON ontology (Wang et al., 2004), OWL Time ontology [4], CoDAMoS ontology (Preuveneers et al., 2004) and Units Ontology (Gkoutos et al., 2012). We use distinguished colors and specific prefix that indicates the ontology that each concept belongs to, in order to differentiate between the reused concepts and the concepts we have proposed. Fig.2 illustrate these concepts as well as the relationships between them. The main concepts of this ontology are:

- **SMSD:Patient:** concept represents the "who" information about the patient. A patient is described as a person and inherits all the properties of the class `FOAF:Person` which is a sub-class of the of the FOAF:Agent class in the FOAF ontology. It include all the demographic information necessary to support the administrative, financial and logistic procedures.
- **SMSD:Device:** concept describes and represents a type of a manufactured item that is used in the provision of healthcare. It could be a medical or non-medical device (Smartphone, Smart Bracelet, Wearable Glucose Level Monitoring device, etc). The property `contains` is used to link between the `SMSD:Device` and the `SSN:Sensor` classes. SSN:Sensor concept is extended from the SSN ontology to represent the physical objects that observe, transforming incoming stimuli into another, often digital, representation(Compton et al., 2012).
- **SMSD:Vital_Signs:** concept describes the detected vital signs of patient which are represented by the four sub-classes

[3] http://xmlns.com/foaf/spec/

[4] https://www.w3.org/TR/owl-time/

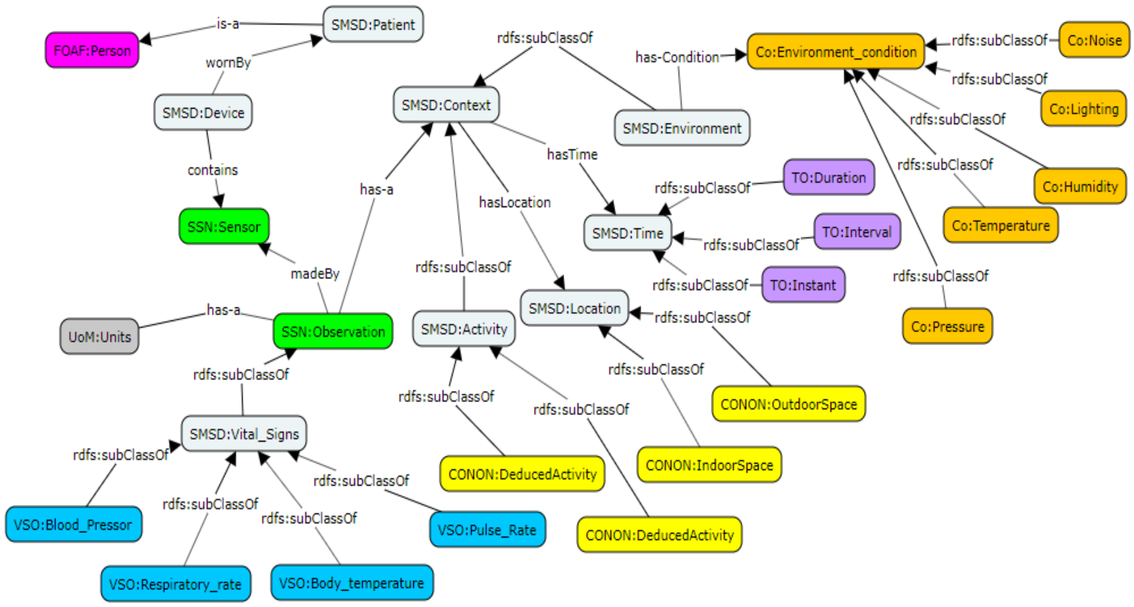

Figure 2: The SMSD ontology.

`VSO:Blood_Pressor`, `VSO:Respiratory_rate`, `VSO:Body_temperature`, `VSO:Pulse_Rate` which are extended by the VSO ontology that covers the four consensus human vital signs: blood pressure, body temperature, respiration rate, pulse rate.

- **SMSD:Context:** concept represents the semantics of concepts and their relationships that captured about a particular context in pervasive computing environments. It provides a simple context modeling based on four main concepts, which are: The Activity, the Location, the Time and the Environment:
  - SMSD:Activity: represents based on several sensors readings the patients activity.
  - SMSD:Location: represents the physical location of the patient.
  - SMSD:Time: represents temporal concepts for describing the temporal properties of the captured data.
  - SMSD:Environment: describes the characteristics of the surrounding environment condition of the patient.

The *SMSD* ontology is encoded in OWL 2 (using Protg 5.5, an open source ontology editor).

3.2 Unstructured EHR Data Integration

It is well known that a lot of relevant data for making accurate healthcare decisions is available in unstructured form. This data needs to be converted into a structured fashion to allow easy analysis.

Advances in artificial intelligence, such as deep learning techniques based on Natural Language Processing (NLP) (Mellish, 1989), enable easy and meaningful information extraction from unstructured data and generate a structured representation.

To make sense of unstructured data, a Named Entity Recognition (NER) (Chieu and Ng, 2003) approach is adopted by the proposed framework. NER is a sub-field of information extraction (IE) that works by searching for specific entity terms and by grouping them into pre-defined categories. Entity recognition has been widely developed in the context of the medical field, usually under the name of Medical Entity Recognition (MER) (Abacha and Zweigenbaum, 2011) in order to identify medical entities.

MetaMap program (Aronson, 2006) developed by the National Institute of Health (NIH) is considered a baseline in MER. *SF4FI-EHR* uses MetaMap to discover and map medical text to UMLS terminologies. *MetaMap*'s output generated from unstructured data is formatted in JSON format, and then transmitted to *FHIR Transform Engine (FTE)* [5] to be converted into FHIR resources. Fig.3 illustrates the described transformation process.

3.3 Structured EHR Data Integration

Structured EHR data are scattered across multiple sources, designed by different data models, encoded with heterogeneous terminologies and represented in

[5] http://www.openmapsw.com/products/FTE.htm

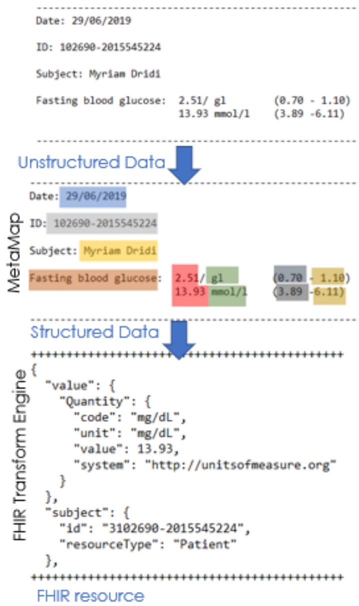

Figure 3: Unstructured EHR data integration process.

various serialization formats. These data need to be extracted from their original sources first, and then restructured into a common format and standard terminologies, in order to make easy their subsequent integration with other data.

A *RESTful FHIR server* based on *FHIR Transform Engine* (FTE) is embedded into our framework, to deal with structured EHR data. Since it is RESTful, the FHIR server can collect data from distributed EHR systems via HTTP GET requests. The data getting in response are represented as JSON-based resources thanks to the FTE.

3.4 The Fully Integrated EHR

To consolidate all parts of the collected data into a single centralized location, and maintain a comprehensive health patient profile, a mapping process is required between the resulted data from the already described processes and the W3C's *FHIR OWL Ontology* [6].

IoT data, modeled using the *SMSD OWL ontology*, are mapped to the FHIR ontology using specific defined mapping rules. For instance, the `SSN:Obersavation` and `SMSD:Activity` from the SMSD ontology are mapped to the `fhir.ResourceObservation` and `fhir.ResourceActivityDefinition`, respectively.

For the other pieces of data (resulted from Unstructured and structured EHR data integration processes) which are already standardized based on FHIR standard, a direct map between their resources elements and the FHIR ontology resources is performed. As a result, a FHIR-based fully integrated EHR that aggregates patient health-related data from disparate sources, is created. Finally, a conversion step is running to map FHIR Resources content from the *FHIR OWL ontology* to their equivalent in the FHIR Relational DataBase schema. Data obtained is stored in FHIRbase, in order to make data available for future purposes.

[6]http://w3c.github.io/hcls-fhir-rdf/spec/ontology.html

4 IMPLEMENTATIONS

As a proof-of-concept implementation, we used: 1) Protg 5.5 to develop the *OWL SMSD ontology* for modeling and semantically annotate IoT raw data, 2) Snoggle as SWRL-based ontology mapper is used to assist in the mapping task between the *SMSD* and the FHIR ontology, 3) *MetaMap* tool is used to recognize medical entities from unstructured data and generate a JSON-based structured output. *MetaMap*'s results is transformed into FHIR-based documents format by using FHIR Transform Engine, 4) *RESTful HAPI-FHIR* server based on FHIR Transform Engine (FTE) is implemented to collect data from distributed EHR systems, and 5) JSON2OWL mapping is developed to map JSON -based data to OWL FHIR ontology. The collected data are stored in *FHIRbase*, as a standard RDB implementation provided by HL7.

5 EVALUATION RESULTS

To validate our work, a clinical data sets relating to 10 patients have been used as input to our framework, comprising for each patient:

- An standardized electronic health record.
- Non-standardized clinical documents (e.g. biological analyzes and radiology reports)
- A vital signs data set generated from different medical devices carried by patient (temperature, blood pressure, heart rate and respiratory rate)
- Readings from patient smartphone multiple sensors that can indicate the patients' activities and his surrounding environment (e.g. GPS, Accelerometer, Ambient Light Sensor, etc.).

The main objective of this evaluation is to exhibit that the health data integration process can be successfully conducted using SF4FI-EHR framework. Each data set will be processed according to its category.

Sensor data are modeled by the modular SMSD ontology, unstructured data are processed by MetaMap and then converted to FHIR resources formats, and structured EHR data are converted to FHIR resources formats, before being directly mapped to the FHIR OWL Ontology. All data collected modeled by the FHIR ontology are storing into *RDB FHIRbase*.

A prototype has been deployed that allowed us to set up a first set of tests using the web browser. SQL queries are executed to demonstrate that the different data resources are successfully integrated together. The SQL query shown in Fig.4 is executed to query for a particular patient observation resources.

```
SELECT resource#>>'{code,text}',
fhirpath(resource, 'dateTime'),
fhirpath(resource, 'value.Quantity.value')
FROM observation
```

Figure 4: The query executed.

The query result is presented in Fig.5, in which we can see that both the blood glucose value from an unstructured/not standardized document (biology analysis results) and the vital signs data from medical devices are both retrieved in the Observation resource section in the new Integrated EHR.

?column?	fhirpath	fhirpath
Body Temperature	2019-06-11T10:37:59	90.582
Pulse Rate	2019-06-11T10:37:59	70.000
Respiration Rate	2019-06-11T10:37:59	13.000
Blood Pressure	2019-06-11T10:37:59	120.000
Blood glucose	2019-06-17T09:38:04	73.788

Figure 5: The result of the query executed.

To make sure that the integration was successfully carried out, we invited domain experts to assist the evaluation process and to assess the quality and the validity of the integrated data. Discussions with experts led to that the integration data is well done, as well as the correctness and the consistency of the integrated data is well ensured.

6 CONCLUSION

In this paper, we described a flexible semantic integration framework called *SF4FI-EHR*. Our solution integrates its data, as well as Unstructured and Structured EHR data, coming from heterogeneous sources. The integration of different data formats is achieved thanks to the application of Semantic Web technologies. A modular *SMSD* ontology based on SSN is proposed to describe its data. *MetaMap* tool is used to deal with the unstructured data, in order to extract meaningful information from these data and generate a structured output. Historical patient data collected from distributed EHR systems using a *Restful FHIR server* based on *FHIR Tranform Engine*. All obtained data are mapped to the *OWL FHIR ontology* to reconstruct a Fully integrated EHR data. The semantic interoperability is handled based on the HL7 FHIR standard.

Future work will focus on evaluating this framework with more real-world use cases for improvement and validation. Furthermore, We planned to improve our approach by integrating environmental data such as Smart Homes and Ambient Assisted Linvig environment data.

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