# A Semantic Cloud-based Knowledge Mediator for Smart Clinical Decision Support System

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**Abstract.** The evolution of the web and mobile applications as well as the proliferation of advanced medical devices underpins the digital healthcare data universe and its distribution. Providing personalized clinical decisions that meet the patient profile requires automatically integrating multiple reliable knowledge sources. However, the dynamicity, the heterogeneity and the distribution of these sources hamper the integration process. In this paper, we have proposed a semantic cloud-based knowledge mediator that allows integrating external knowledge sources independent of their knowledge representation and used syntax. To this end, the proposed architecture defines a common semantic representation of the knowledge sources' characteristics in order to dynamically adapt the queries and retrieve the appropriate knowledge from external sources. We have illustrated the efficiency of our proposed architecture through a diabetes scenario considering comorbidity condition.

## 1 Introduction

The integration of Information Technology (IT) in the healthcare sector fosters the remote access to healthcare services and accelerate the delivery of care. It has proven efficiency in managing chronic diseases, engaging the patient in the care process, and improving outcomes. However, according to the World Health Organization (WHO), the number of patients with chronic disease keeps growing (Abegunde and Stanciole, 2006). Thus, early and systematic interventions are highly recommended to prevent health complications and reduce the disease spread. Medical prevention requires continuously monitoring the patient health and providing advanced mechanisms that predict if health complications may occur.

New generation of healthcare technologies including wearable devices contribute to enhancing the quality of life (Park and Jayaraman, 2003) by providing real-time data collection pertaining to the patient health and behavior. Emerging these personal technologies help accelerating and improving the healthcare and economic outcomes. Likewise, advances in internet and web technology have been exploited in healthcare to make an increasing quantity of information sharable and reusable by the healthcare practitioners. Many reliable healthcare distributed knowledge sources such as drugbank, sider effect and clinical trials are being published to facilitate seeking the appropriate information. Integrating these sources within the clinical decision support systems is required to automatically leverage from available and trusted knowledge sources to assist the physicians in selecting the right patient treatment plan. The main goal is to meet the patient's medical conditions, to avoid drug interactions and to reduce the treatment cost. In an earlier work (Mezghani et al., 2014), we discussed a new vision of knowledge-based CDSS that aims at adapting the patient treatment plan based on the autonomic computing paradigm that automatically monitors, analyzes the collected data, and generates the treatment recommendations to assist the physicians based on the domain knowledge. It is worth mentioning that the physician approval is required, since he/she is the responsible of the patient health. In this paper, we concentrate on the integration of various accessible external knowledge sources to provide accurate decision.

The heterogeneity and the distribution of the medical knowledge remain challenging. This heterogeneity is not limited to knowledge representation, but also includes the semantic used to represent the meaning of the information. Traditional CDSS are not able to support this diversity. The integration of a new knowledge source requires maintaining the systems and developing its appropriate application to retrieve the information, which is challenging due to the rapid growth of the quantity of knowledge being published.

Consequently, we propose a semantic cloud-based knowledge mediator named *KaaS Broker* that aggregates heterogeneous knowledge sources in order to provide accurate information. Our knowledge mediator covers the heterogeneity of knowledge structure and meaning through using a common conceptualization of the knowledge providers' characteristics based on the semantic web standards coupled with cloud computing technologies to guarantee the system scalability when querying and aggregating the knowledge.

The rest of the paper is organized as follow. Section 2 details works dealing with clinical decision support systems, delineates the status of linked data in healthcare as a source of information, and identifies solutions related to knowledge integration. Section 3 portrays our proposed knowledge mediator and describes its internal components. Section 4 describes the use of our *KaaS Broker* to manage the treatment of a patient having diabetes. Finally, Section 5 summaries our contribution and describes our future work.

# 2 Related Work

In this section, we focus on providing an overview about the clinical decision support systems, identifying accessible and reusable healthcare knowledge, and finally describing existing solutions that propose integrating distributed knowledge sources.

## 2.1 Clinical Decision Support Systems

Clinical decision support systems (CDSS) have shown great efficiency in managing patients' health and providing personalized treatment based on Information Technologies. The main goal of CDSS is to assist clinical practitioners to take the right decision by providing "*computer-generated clinical knowledge and patient-related information, intelligently filtered or presented at appropriate times, to enhance patient care*" (Osheroff et al., 2005). CDSS may focus on monitoring (provide patient profile including the treatment history, the observations, etc.), diagnosing patient health (detect or predict which disease or new symptom the patient is developing), and generating clinical recommendations (recommend and suggest the appropriate treatment based on patient profile) (Wright and Sittig, 2008). The development of CDSS is classified into two categories: *knowledge-based* and *non-knowledge-based* systems (Berner and La Lande, 2007). Knowledge-based CDSS relies on a conceptualization of the medical knowledge encoded in a computer interpretable format, while the non-knowledge-based CDSS uses machine learning and other statistical pattern recognition approaches that allow the computer automatically learning from past experiences and/or detecting patterns from the clinical data.

We are interested in knowledge-based CDSS where the knowledge is extracted and formalized based on clinical guidelines and/or the medical experts' knowledge. The work of (Sanchez et al., 2011) delineates a knowledge-based tool that assists the physicians in diagnosing and detecting the Alzheimer Disease (AD). The proposed tool aims at gathering multidisciplinary knowledge such as SNOMED CT, MIND ontology and SWAN ontology, inferring and reasoning over the underlying knowledge bases for the decision making process. The system is based on production rules provided by domain experts to generate suggestions. The work of (Yao and Kumar, 2013) describes a knowledge-based CDSS named CONFlexFlow that formalizes the clinical knowledge using ontologies and SWRL to encode rules for user-defined reasoning. The authors identified different types of rules to evaluate the patient status such as Patient Treatment Rules and Prescription Rules to detect drug-drug interaction. Similar to (Yao and Kumar, 2013), we aim at providing accurate decision by considering interactions. However, in their work, the drug-drug interaction knowledge need to be manually encoded. Our work proposes mechanisms that automatically seek the information from external heterogeneous knowledge sources such as DrugBank and sider effect and integrate them to dynamically generate the treatment and prevent complications.

As the medical knowledge evolves rapidly, updating the knowledge base of CDSS is a tricky task, especially if this new knowledge is represented differently and uses different semantics. Thus, a new CDSS approach that interconnects heterogeneous and distributed knowledge sources is required for accurate decision making.

## 2.2 Healthcare Linked Data for CDSS

Recently, large Linked Data sources in different domains have become available. Linked data refers to enabling the extension of the Web with a global data space based on open standards - the Web of Data. It provides a common data model that makes it possible to implement generic applications that operate over the complete data space (Heath and Bizer, 2011). From the implementation perspective, linked data uses RDF as a standardized data representation format, and HTTP as a standardized access mechanism (Jentzsch et al., 2009). Different endpoints have been proposed to extract the data using the SPARQL query language. Table 1 cites examples of available medical linked data sources which are useful for the decision support system. For instance, Bio2RDF (Belleau et al., 2008) offers different SPARQL endpoints to DrugBank and Sider Effect to respectively extract drug-drug and food-drug interactions, and the side effects of a specific drug. Freebase is another large knowledge base that can be consumed to retrieve the symptoms, risk factors and treatments of a disease. It is worth mentioning that the extracted data from Freebase must be approved by the medical experts in order to be automatically reused, since the knowledge is populated by community users and retrieved from web sites. Some other efforts have focused on integrating multiple existing linked data into a common repository such as life linked data which integrates 25 popular biomedical data sources.

| *#Context* | *#Official Source* | *#Sparql Endpoints* |
|---|---|---|
| Drug-Drug Interaction | Drugbank: http://www.drugbank.ca/ | http://drugbank.bio2rdf.org/sparql http://wifo5-03.informatik.uni-mannheim.de/drugbank/snorql/ |
| Drug-Food Interaction | Drugbank: http://www.drugbank.ca/ | http://drugbank.bio2rdf.org/sparql |
| Drug Side Effect | SIDER Effect: http://sideeffects.embl.de/ | http://sider.bio2rdf.org/sparql http://wifo5-03.informatik.uni-mannheim.de/sider/snorql/ |
| Treatment, Symptoms, Risk Factors | Freebase: http://www.freebase.com/ | http://lod.openlinksw.com/sparql |
| UMLS, Gene,Protein, etc. | Linked Life Data: http://linkedlifedata.com/ | http://linkedlifedata.com/sparql |

TAB. 1 – *Example of Available Healthcare Linked Data for CDSS.*

The work of (Ostankov et al., 2014) proposes a Linked Health Answers system for question answering. This system implements mechanisms that transform natural language questions into formal semantic request <?s,?p,?o> (taking the form of RDF triple) based on NLP tools and machine learning-based algorithm. The authors integrated UMLS to identify the concepts using the life linked data sparql endpoint. Once the request is transformed, it will be invoked over the ontology connector (e.g. Linked life Data, FreeBase and DBpedia). The work of (Jentzsch et al., 2009) is an interesting work in the pharmaceutical industry where the authors referred to LinkedCT, DrugBank and Diseasome repositories in order to integrate accessible data related to companies, drugs, diseases and genetic variation, and continuously keep the user up-to-date with the available extra data without mapping synonyms and identifiers.

Both the work of (Jentzsch et al., 2009) and (Ostankov et al., 2014) are mainly based on linked data to provide more accurate information from distributed knowledge represented in RDF. However, they didn't tackle the problem of integrating at runtime a new knowledge source representing the knowledge with a new structure and reusing it to provide personalized and accurate decision.

## 2.3 Knowledge Integration

Knowledge integration enables the coordination of functional expertise and activities to refine and create knowledge (Devadoss et al., 2005). The mediator architecture represents a potential solution for knowledge integration adapted in different domains to interconnect heterogeneous sources (Leclercq et al., 1999) (Romanello et al., 2005). A mediator is defined (Wiederhold, 1992) as "*a software module that exploits encoded knowledge about some sets or subsets of data to create information for a higher layer of applications*". Various methods and tools were proposed to define the mediator architecture. Ontologies and vocabulary standards are the most used methods within a mediator to support semantic data integration, cope with data heterogeneity and guarantee interoperability among information systems (Sujansky, 2001), since they serve as a semantic reference for system programmers and users (Lenz et al., 2007).

(Bergamaschi et al., 2001) proposed a semi-automated approach based on the Description Logic-based language for the extraction and the integration of heterogeneous information sources. The proposed approach has been implemented in the MOMIS (Mediator envirOnment for Multiple Information Sources) system that follows a semantic approach to integrate information based on the conceptual schemas of the information sources, and on a mediator component. Another interesting work tackling the healthcare decision making domain is the work of (Belian and Salgado, 2010). The authors proposed a contextual representation of the structured and semi-structured data sources based on ontology that will be implemented for a mediator-based information integration system named GAV. Similar to (Belian and Salgado, 2010), our proposed architecture aims at providing a common contextual representation of the data sources based on ontology. Thus, knowledge providers should follow the semantic model provided by the *KaaS Broker* to annotate their schema and align their lexical terms. Our work is wider than (Belian and Salgado, 2010), since it also characterizes the endpoints of these data sources, the languages they use to represent data, and identifies components to adapt the queries to extract the knowledge from the external sources.

In the same context, (Azami et al., 2012) proposed a mediation architecture that includes mainly two components: the Mediator and the Adapter. The mediator, which is associated to an applicative domain, describes and combines the data based on ontology that unifies the clinical vocabularies and the medical concepts. The Adapter plays the role of the interface between the mediator and the database to match the data format and retrieve the data. However, according to the authors, for each new data/information source, an adapter must be developed. This makes the architecture not flexible enough to support the dynamic evolution of the information sources. Both (Azami et al., 2012) and (Belian and Salgado, 2010) do not integrate external linked data sources to extract online information when taking the decision.

In our work, we provide smart mechanisms that select the right knowledge sources, retrieve and aggregate the information for accurate decision. By characterizing the knowledge source, our mediator is able to automatically adapt the query, without developing a specific adapter. In the next section, we detail our mediator with its internal components.

## 3 A Semantic Cloud-based Knowledge Mediator: Application to Healthcare

In healthcare, multiple and various knowledge sources are available. Their heterogeneity is not limited only to the type of the knowledge; it includes also the representation format and the lexical dimension. The framework proposed in this paper addresses this challenge through providing a semantic knowledge mediator that allows integrating various sources that will be used for elaborating the patient treatment. In our previous work (Grolinger et al., 2015), we extended the NIST Cloud Computing reference architecture (Liu et al., 2012) with a new layer named Knowledge as a Service (KaaS) that aims at extracting knowledge from distributed data stored in cloud environment. We identified the *KaaS Broker* as an extension of the basic *Cloud Broker* defined by the NIST cloud computing reference architecture (Liu et al., 2012) in order to aggregate heterogeneous knowledge sources deployed in a cloud environment. In this paper, we deepen the *KaaS Broker* architecture by identifying new components which are able to select the right knowledge provider offering the required information, independent from its structure and format.

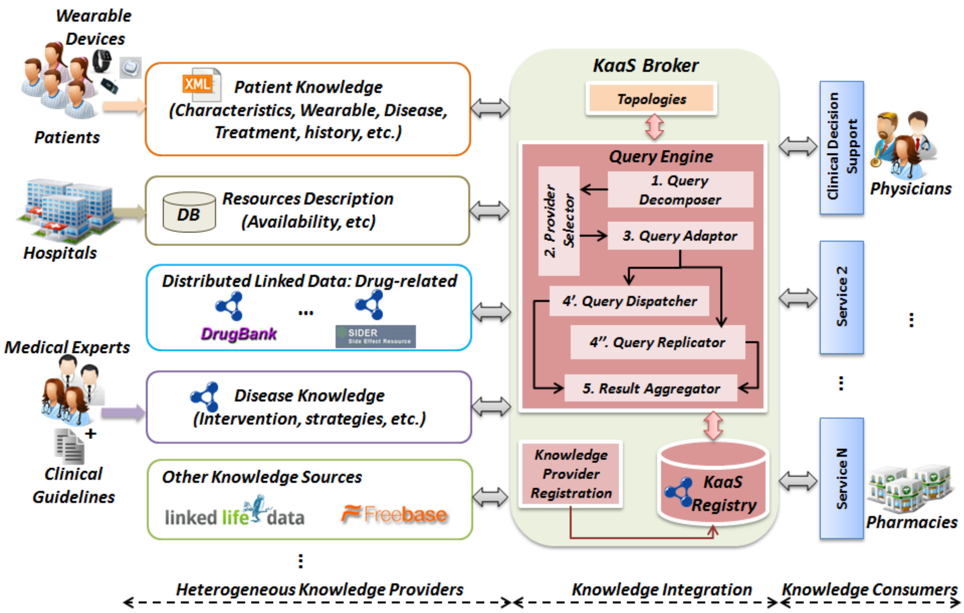


FIG. 1 – *A Semantic Cloud-based Architecture for Smart Healthcare Management.*

The *KaaS Broker* plays the role of the mediator among the knowledge providers. Figure 1 portrays the proposed semantic cloud-based architecture and details its main internal components that allow integrating heterogeneous knowledge providers. The proposed architecture is mainly composed of three layers: the "*Heterogeneous Knowledge Providers*" or *KaaS Providers* publish their knowledge to be consumed according to access control topologies; the "*Knowledge Integration*" includes the *KaaS Broker* which represents the fundamental element for knowledge aggregation and is part of the *Cloud Broker* (Grolinger et al., 2015); and finally the "*Knowledge Consumers*" or *KaaS Consumers* are services connected to the *KaaS Broker* and express their requirements to be processed and redirected to the right "*Knowledge Providers*".

## 3.1 Knowledge Providers

Automating clinical decision-making is quite tricky since it must take into consideration at the same time different types of healthcare knowledge. For instance, to generate the right personalized treatment plan, the following knowledge sources are required:

– ***Patient Knowledge*** includes a clear description of the patient health status including the current diseases and their severity, the current treatments, his/her medical history and characteristics such as allergies. It also includes the patient preferences to provide more personalized decisions. The integration of wearable devices that capture individualized data are also described in this knowledge since they are personal technologies that contribute to generating new knowledge about the patient such as health complications. The patient knowledge, in general, is encoded in Electronic Health Records that can be represented with XML based on standards such as OpenEHR [1] , or HL7 RIM [2] version 3, etc.
– ***Resources Knowledge*** describes the availability of the hospitals resources including equipments and medical stuffs that may be required for the execution of the patient treatment. Accessing to both the patient and resource knowledge are based on access control policies that will be described in the *KaaS Broker*.
– ***Disease Knowledge*** is the core domain knowledge describing the theories about the clinical conditions such as the disease, symptoms, risk factors, the parameters to monitor, the interventions with their characteristics such as contraindications, their types ('drug', 'surgical', 'physical', etc.), etc. Based on this knowledge, the interventions will be identified and filtered to meet the patient characteristics in order to avoid possible interactions. In general, the disease knowledge is encoded in the Clinical Guidelines, which are free text documents, or located in the medical experts' minds. Recent researches focused on formalizing the medical knowledge using ontology (Jovic et al., 2007) or based on existing Computer Interpretable Guideline (CIG) (de Clercq et al., 2004) such as Arden syntax in order to be automatically reused by computers through reasoning engines.
– ***Drug Knowledge*** describes the drug chemical compositions, the different interactions with other drugs or with foods. It also includes the drug side effects that may accentuate the current disease. Such information is required in the decision support system to provide personalized treatment and avoid complications. Drug-related knowledge can be represented with RDF as linked data, which is the case of the DrugBank and SIDER Side Effect Resource databases, and queried through sparql endpoint.

1. OpenEHR: http://www.openehr.org/
2. HL7 RIM version 3: http://www.hl7.org/implement/standards/product_brief.cfm?product_id=77

It is axiomatic that integrating these heterogeneous knowledge sources is required for better decision making, but it is also challenging. Consequently, we propose the *KaaS Broker* that understands the meaning of the knowledge providers, automatically retrieves and aggregates the results for better information.

## 3.2 KaaS Broker

The *KaaS Broker* is the main component responsible of integrating heterogeneous knowledge providers and generating the right knowledge to the consumers. It plays an important role in guaranteeing the interoperability. To deal with the heterogeneity of knowledge providers, our *KaaS Broker* implements a common representation that allows annotating the Knowledge Providers' characteristic in order to be reused when selecting the appropriate provider and rewriting (adapting) the queries according to the provider language.

Each *Knowledge Provider* needs to subscribe to the *KaaS Broker* through the "Knowledge Provider Registration" service that allows annotating the knowledge provider characteristics. All these annotations are stored in the "KaaS Registry" which implements an ontology describing providers' characteristics such as properties including the endpoint to access to the knowledge, where it is stored, the language used to represent this knowledge and to query it, and the meaning of the data. Table 2 presents an excerpt of annotating the Bio2RDF DrugBank and the University of Mannheim knowledge sources describing drug-drug interactions.

The *KaaS Broker* understands the meaning of the knowledge providers based on the ontology implemented in the "KaaS Registry" independent of the used syntax and representation. Thus, it can dynamically select the right provider to answer the consumer requirements. The main objective of the "KaaS Registry" is to provide a common conceptualization and representation of the disparate heterogeneous knowledge sources in order to be queried and integrated through the "Query Engine". This later is responsible of decomposing and adapting the queries according to the Knowledge Provider characteristics. Knowledge consumers such as physicians or CDSS are also subscribed to the *KaaS Broker* to leverage from the information completeness for better decision making. When a consumer sends a request to the *KaaS Broker*, the request is intercepted by the "Query Engine" which is mainly composed of six sub-components: the "Query Decomposer", "Provider Selector", "Query Adaptor", "Query Dispatcher", "Query Replicator", and "Result Aggregator".

The "Query Decomposer" decomposes the request to identify the main entities that need to be retrieved. According to the identified entities, the *KaaS Broker* refers to the "KaaS Registry" to select where the information about these entities can be found. As the Knowledge Provider is characterized in the "KaaS Registry", the "Provider Selector" component retrieves from the "KaaS Registry" the endpoint, the query language, etc. the appropriate knowledge provider(s) to the "Query Adaptor". This later will rewrite the queries after checking if the consumer has access to the selected Knowledge Provider services based on the "Access Control Topologies" component. If it is the case, the query is sent to the provider.

Sending queries to Knowledge providers is driven by Quality of Service (QoS) topologies that refer to satisfying the contract between the Knowledge Consumers and the KaaS Broker. An example of contract is getting a response time less than 10 seconds. Depending on the QoS, the dispatching or the replication mechanism will be deployed respectively through the "Query Dispatcher" and the "Query Replicator" components. The returned results will be aggregated using the "Result Aggregator" component and delivered to the knowledge consumer. In the next

| *Knowledge Sources* | Bio2RDF Drug Bank | University of Mannheim |
|---|---|---|
| *HasEndpoint* | http://drugbank.bio2rdf.org/sparql | http://wifo5-03.informatik.uni-mannheim.de/drugbank/snorql/ |
| *HasLanguageRep* | RDF | RDF |
| *HasQueryLang* | SPARQL | SPARQL |
| *HasPrefix* | dv:<http://bio2rdf.org /bio2rdf.dataset_vocabulary:><br>dr:<http://bio2rdf.org /drugbank_vocabulary:> | drugbank:<http://wifo5-04.informatik.uni-mannheim.de/drugbank /resource/drugbank/> |
| *Class:Drug* | http://bio2rdf.org/drugbank _vocabulary:Drug | http://wifo5-04.informatik.uni-mannheim.de/drugbank /resource/drugbank/drugs |
| *Class: Drug-Interaction* | http://bio2rdf.org/drugbank _vocabulary:Drug-Drug-Interaction | http://wifo5-04.informatik.uni-mannheim.de/drugbank/resource /drugbank/drug_interactions |

TAB. 2 – *An excerpt of the knowledge sources characterization for knowledge integration.*

section, we illustrate the efficiency of our proposed architecture to manage medical interactions for a patient having hyperglycemia in type 2 diabetes.

# 4 Diabetes Scenario

Motivated by the rapid growth of the number of patients having type 2 diabetes (Whiting et al., 2011) and the growth of medical errors (Henriksen et al., 2005), we propose to integrate our architecture to demonstrate how to manage the patient treatment by integrating external medical knowledge sources. Preventing diabetes complications requires not only continuously monitoring the glucose level, but also providing a personalized treatment that takes into consideration the patients characteristics and comorbidity. Avoiding medical interaction is one of the strategies that reduces medical errors and provides a better quality of care to patients. For instance, we consider a patient having type 2 diabetes. He is overweight (BMI>30) and he is taking 'Meglitinides' and the 'Aripiprazole' to treat respectively hyperglycemia and schizophrenia.

During a consultation, the physician measures the patient blood sugar level and detects an increased value that exceeds the patient goal. Consequently, the physician decides to recommend a new treatment to his patient. The added value of our proposal is that it dynamically seeks online medical information that may highly impact on the decision. Figure 2 presents a sequence diagram describing the behaviour of our proposed *KaaS Broker*.

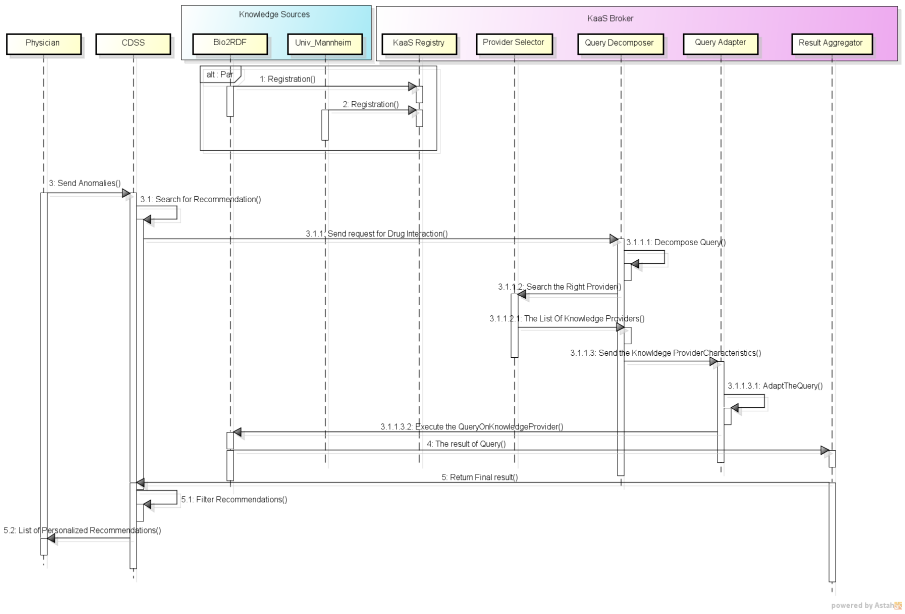


FIG. 2 – *An example of the* KaaS Broker *behaviour when it is solicited by a CDSS.*

All the external knowledge sources should be registered in the "KaaS Registry" in order to be later exploited by the *KaaS Broker*. When the physician introduces the detected anomaly in the CDSS, the CDSS binds to the "Query Decomposer" that allows creating the request based on the KaaS Registry Ontology. After the decomposition, the selection of the provider is done based on the characterized knowledge sources. In our case, the following query (Listing 1) selects the first knowledge source with its characteristics (endpoint, query language and prefixes) that contains information related to the drug-drug interactions.

Listing 1 – *Example of SPARQL query to search for Knowledge Source*

```
SELECT ?endp ?lang ?prefix WHERE {
?s rdf:type cat:KnowledgeSource.
?s prop:HasEndpoint ?endp.
?s prop:Represent ?entity.
?s prop:HasQueryLang ?lang.
?s prop:HasPrefix ?prefix.
?entity prop:HasCategory ?dr.
FILTER(REGEX(?dr,"DrugInteraction")).
} LIMIT 1
```

Based on the generated endpoint (in our case it is the Bio2RDF drugbank knowledge source), the "Query Adaptor" transforms the query according to the knowledge provider appropriate language's (in this example it is SPARQL), and sends the transformed query (Listing 2) to the provider to retrieve knowledge. This query asks for the list of antihyperglycemic drugs that should not be prescribed to the patient based on his current treatment (Aripiprazole). Within the *KaaS Broker*, we implemented the SPARQL queries using the Jena Ontology API [3] to connect to the distributed knowledge sources via there SPARQL endpoints and detect interactions.

Listing 2 – *SPARQL query that detects interaction with the 'Aripiprazole' and antihyperglycemic drugs*

```
#Connect to the Prefixes for the query execution
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX void: <http://rdfs.org/ns/void#>
PREFIX dv: <http://bio2rdf.org/bio2rdf.dataset_vocabulary:>
#Connect to the Bio2RDF endpoint
PREFIX dr:<http://bio2rdf.org/drugbank_vocabulary:>
#Connect to the DrugBank Bio2RDF endpoint
SELECT distinct ?ddi ?description WHERE {
?drug_uri rdf:type dr:Drug.
?drug_uri rdfs:label ?label.
#Find all interactions with 'Aripiprazole'
?ddi rdf:type dr:Drug-Drug-Interaction .
?ddi rdfs:label ?description.
?drug_uri dr:ddi-interactor-in ?ddi.
FILTER regex(?label, 'Aripiprazole').
#Select only interactions with hyperglycemia drugs
?drug_diab dr:ddi-interactor-in ?ddi.
?drug_diab dcterms:description ?lab1.
FILTER regex(?lab1, 'hyperglycemic').}
```

Figure 3 represents the list of interactions that should be avoided. This list is sent to the CDSS in order to take into consideration these interactions when filtering the recommendations to generate the appropriate and personalized recommendations meeting the patient profile.

# 5 Conclusion

Providing accurate decision concerning the patient treatment plan strongly depends on the quality and completeness of the knowledge on which the decision process operates. Advances in web technologies make many reliable medical knowledge available on the web and accessible based on standard languages. In this paper, we detailed some existing reusable sources in the context of clinical decision support system. Then, we proposed a semantic cloud-based knowledge mediator that integrates heterogeneous knowledge providers. The proposed mediator implements mechanisms that understand the meaning of the represented knowledge, search

3. https://jena.apache.org/documentation/ontology/

```
------------------ Detected Interaction 1------------------
Interaction URL: http://bio2rdf.org/drugbank_resource:DB00331_DB01238
Description: DDI between Metformin and Aripiprazole - Hyperglycemia-Associated Agents may
diminish the therapeutic effect of Antidiabetic Agents.
------------------ Detected Interaction 2------------------
Interaction URL: http://bio2rdf.org/drugbank_resource:DB00672_DB01238
Description: DDI between Chlorpropamide and Aripiprazole - Hyperglycemia-Associated Agents may
diminish the therapeutic effect of Antidiabetic Agents.
------------------ Detected Interaction 3------------------
Interaction URL: http://bio2rdf.org/drugbank_resource:DB00912_DB01238
Description: DDI between Repaglinide and Aripiprazole - Hyperglycemia-Associated Agents may
diminish the therapeutic effect of Antidiabetic Agents.
------------------ Detected Interaction 4------------------
Interaction URL: http://bio2rdf.org/drugbank_resource:DB01016_DB01238
Description: DDI between Glyburide and Aripiprazole - CYP3A4 Inhibitors (Weak)
may increase the serum concentration of ARIPiprazole.
------------------ Detected Interaction 5------------------
Interaction URL: http://bio2rdf.org/drugbank_resource:DB01120_DB01238
Description: DDI between Gliclazide and Aripiprazole - Hyperglycemia-Associated Agents may
diminish the therapeutic effect of Antidiabetic Agents.
```

FIG. 3 – *An excerpt of the list of interactions between the current patient treatment (Aripiprazole) and the antihyperglycemic drugs.*

and aggregate distributed knowledge in order to provide the right decision meeting the patient characteristics. We delineated the behaviour of our *KaaS Broker* through a diabetes scenario.

Our future work focuses on evaluating the performance of our *KaaS Broker* and the impact of adapting queries on the quality of service such as the response time when integrating various knowledge sources.

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