

# RML based ontology development approach in internet of things for healthcare domain

Ontology  
development  
approach

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Jameel Ahamed

*Department of Computer Science and Engineering,  
National Institute of Technology, Srinagar, India and Department of CS&IT,  
Maulana Azad National Urdu University, Hyderabad, India*

Roohie Naaz Mir

*Department of Computer Science and Engineering,  
National Institute of Technology, Srinagar, India, and*

Mohammad Ahsan Chishti

*Department of Computer Science and Engineering,  
National Institute of Technology, Srinagar, India and Department of IT,  
School of Engineering and Technology, Central University of Kashmir, Kashmir, India*

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## Abstract

**Purpose** – A huge amount of diverse data is generated in the Internet of Things (IoT) because of heterogeneous devices like sensors, actuators, gateways and many more. Due to assorted nature of devices, interoperability remains a major challenge for IoT system developers. The purpose of this study is to use mapping techniques for converting relational database (RDB) to resource directory framework (RDF) for the development of ontology. Ontology helps in achieving semantic interoperability in application areas of IoT which results in shared/common understanding of the heterogeneous data generated by the diverse devices used in health-care domain.

**Design/methodology/approach** – To overcome the issue of semantic interoperability in healthcare domain, the authors developed an ontology for patients having cardio vascular diseases. Patients located at any place around the world can be diagnosed by Heart Experts located at another place by using this approach. This mechanism deals with the mapping of heterogeneous data into the RDF format in an integrated and interoperable manner. This approach is used to integrate the diverse data of heart patients needed for diagnosis with respect to cardio vascular diseases. This approach is also applicable in other fields where IoT is mostly used.

**Findings** – Experimental results showed that the RDF works better than the relational database for semantic interoperability in the IoT. This concept-based approach is better than key-based approach and reduces the computation time and storage of the data.

**Originality/value** – The proposed approach helps in overcoming the demerits of relational database like standardization, expressivity, provenance and supports SPARQL. Therefore, it helps to overcome the heterogeneity, thereby enabling the semantic interoperability in IoT.

**Keywords** RDF, Ontology, SPARQL, Internet of things, Semantic interoperability

**Paper type** Research paper



## 1. Introduction

The Internet of Things (IoT) is a collection of physical objects known as things that are embedded with sensors, software and other technologies to communicate and exchange data with other devices and systems over the internet. The devices used in IoT are heterogeneous

in nature and requires interoperability for their use in diverse applications. Platform, network, syntactic, semantic and device interoperability are the common types of interoperability in the IoT. Besides interoperability, IoT data security is also a challenge as this data is keeps on communicating among various devices (Khari *et al.*, 2020).

### *1.1 Semantic interoperability in Internet of Things*

Semantic Interoperability is the capability of two or more than two systems to interchange the information via a common understanding. This knowledge can be enacted automatically and accurately. So, the semantic interoperability needs a shared meaning of the data being interchanged at the semantics level maintaining the semantics of the original information. There is still a need to retain intrinsic information from data sources, preserve domain knowledge and promote data conservation, despite the adoption of shared ontologies and vocabulary that allow the representation and sharing of meaning. The conservation of shared ontologies, which involves a centralized and periodic updating process, is another problem of semantic interoperability. Finally, the software architecture focused on shared ontologies, a well-known open issue of the Semantic Web, still has problems related to scalability. The data generated in different formats by IoT devices hinders the interoperability of applications and platforms that are unable to interpret the data, acting inconsistently on the information obtained. In this context, the use of common vocabulary is important to be able to explain the significance of data in this setting (Jabbar *et al.*, 2017). In brief, semantic interoperability occurs due to diverse nature of data generated by heterogeneous IoT devices (Venceslau *et al.*, 2019).

Health-care domain is one of the emerging application areas of IoT that has evolved into smart-health system having typical mobile devices (such as smartphones) which are used in conjunction with wearable medical devices (such as blood pressure monitors, glucometers, smart watches, smart contact lenses, biomedical sensors) and IoT gadgets (such as implantable or ingestible sensors) for continuous patient observation and treatment at homes or medical centers (Zeadally *et al.*, 2019). The data collected by smart objects is heterogeneous (of different formats) in nature and needs semantic interoperability to have shared understanding/common meaning (Jagadeeswari *et al.*, 2018).

## **2. Related work**

Interoperability in IoT is one of the major challenges when it comes to the application of the IoT. In this regard, Noura, Atiquzzaman and Gaedke (2019) defined that 40% of the benefits of IoT can be achieved by having the successful interoperability among the system pertaining to IoT. Pal and Yasar (2020) defined an algorithm for presenting the description logics-based entity definition similarity evaluation to promote semantic web service interoperability. Al-Shdifat *et al.* (2020) performed an experiment for the development of a framework for creating a context resolution service for IoT-enabled industrial diagnostics. Balakrishna and Thirumaran (2019) demonstrated the semantic interoperability in IoT and big data for health care domain. Rahman and Hussain (2020) developed a light weight dynamic ontology using the clustering technique which give dynamic semantics automatically to have more concepts using machine learning techniques. Mahria, Chaker and Zahi (2020) described a mechanism for development of ontology from relational database on the pattern of existing system and also describes an evaluation process for ontologies using TBox and ABox approach. There are many approaches for the development of ontologies, but to evaluate them, an evaluation criteria/tools are required. Raad and Cruz (2018) demonstrated the challenge of searching an accurate ontology evaluation method by using the already available ontology evaluation mechanisms. The authors divided the mechanism of ontology evaluation into four types: gold standard-based, corpus-based, task-based and criteria based scheme. Malik *et al.* (2016) explained the

mechanism and processes followed in Big Data for the transformation of heterogeneous data to semantically enriched simplified data using RDF, RDFS. Jozashoori *et al.* (2020) suggested FunMap which is a class of function-based mapping languages that uses a collection of lossless rewriting rules to push down and materialize function execution in the early stages of knowledge graph creation. Ganzha *et al.* (2018) presented a mechanism to identifier management and potential ID interoperability architectures built as part of the INTER-IoT project. Chaves-Fraga *et al.* (2019b) contributed an empirical configuration which can be reemployed for the assessment of knowledge graph development tools and mapping languages (e.g. SPARQL-Generate, TARQL or R2RML). Dimou, Sande, Slepicka *et al.* (2014) presented a mechanism presented the RML mapping language, an extension of R2RML, as a framework for mapping heterogeneous and hierarchical data sources into RDF (the W3C standard for mapping relational databases into RDF). Venceslau *et al.* (2019) described the state-of-the-art of IoT semantic interoperability and analyzing the Semantic Web technologies. Jozashoori and Vidal (2019) defined MapSDI, a mapping rule-based architecture for optimizing semantic data integration into knowledge graphs, addressed the issues of knowledge graph construction at scale. MapSDI efficiently enriches massive, heterogeneous and potentially low-quality data with semantic information. Chen *et al.* (2020) proposed a paradigm for modeling the IoT's real-time dynamic ontology semantic dimension architecture model. Chaves-Fraga *et al.* (2019a) defined an applied method for the use and utilization of declarative mappings for the publication of open transport data from transportation authorities and operators into a transmodel ontology. Dimou, Sande, Colpaert *et al.* (2014) introduced the RML mapping language, a standardized language built on top of the W3CS R2RML specification for mapping relational databases to RDF. Iglesias *et al.* (2020) proposed SDM-RDFizer, an RDF Mapping Language (RML) interpreter that converts raw data in various formats into an RDF information graph. Gyrard, Serrano and Atezing (2015) presented the semantic web methodologies, best practices and recommendations beyond the IERC Cluster Semantic Interoperability (IERC AC4). Rhayem, Mhiri and Gargouri (2020) provide a review of IoT data, IoT services, IoT data and services, IoT Security and Web of Things. Baqa *et al.* (2019) described the types of IoT systems that can be developed with semantic technologies, allowing applications to reuse knowledge that was originally given for a particular application or IoT domain. Azevedo, Pereira and Henriques (2019) proposed a generalized method for mapping a relational database to an ontology and evaluating the created ontology's correctness. Turchet *et al.* (2020) defined IoMusT Ontology which was introduced in OWL for describing ecosystems developing around IoMusT technologies.

From the literature review, it is concluded that semantic interoperability can be overcome and minimized by the development of ontology-based approach for the desirable applications. This approach is applicable in all application areas of IoT like health-care system, industrial system, transport system, e-commerce and other relevant areas.

### 3. Semantic interoperability: a proposed system

In this system, the authors concentrated on the tracking and monitoring of patients with chances of having cardiovascular diseases. Patients provide the data through user interface and biomedical sensors. The data generated is heterogeneous in nature and needs semantic interoperability for the use in the IoT based health-care applications. For Semantic Interoperability, the diverse data is mapped to common format (RFD) using configuration and mapping criteria's. The data in RDF format then uploaded on GraphDB repository. Thereafter, SPARQL queries are written keeping in view the competency questions for the retrieval of the information. The next step is to use this data in the health-care system for the diagnosis of the diseases in patients by experts located at a different location from the

patient. Cloud Platforms (Vimal *et al.*, 2020) are also used to store patient incidence data for ongoing tracking. With the aid of IoT equipment and UI, doctor and patient communicate to one another. Doctor can remotely track and diagnose patients located at any far place, wherever, and with no limitation of the smart objects/devices made from particular vendors. Hence, semantic interoperability deals specifically with the section on user interface.

A major problem is interoperability between IoT devices from various vendors. The sharing of knowledge with meaningful and understandable definitions is semantic interoperability (Jabbar *et al.*, 2017).

By inserting packages of self-described information into data, it involves semantics. Semantic interoperability is a technique for ensuring interoperability between IoT products from different vendors. To make shared vocabulary meaningful, IoT devices take UI data and add semantic annotations from the semantic section.

Data analytics is a data science technique that uses raw data to draw clear conclusions. It results in cost savings as well as quicker and better decision-making. Data analytics is used to analyse data collected from IoT devices. Then, to make it more relevant and cost-effective, semantic annotations were added. Figure 1 depicts the proposed architectural model for IoT semantic interoperability.

For the realization of the proposed model, the dataset is collected from Kaggle and UCI repository. The data is pre-processed using missing data handling techniques like mean, median, mode and is defined in Table 1 ((Figures 2–3)

**Competency questions:** The CQs are defined as natural language questions that represent an informal requirement within a particular domain. They represent the knowledge that the ontology should cover. Competency questions are very important for the retrieval of desirable information. The following are the CQs with their corresponding SPARQL queries for this ontology.

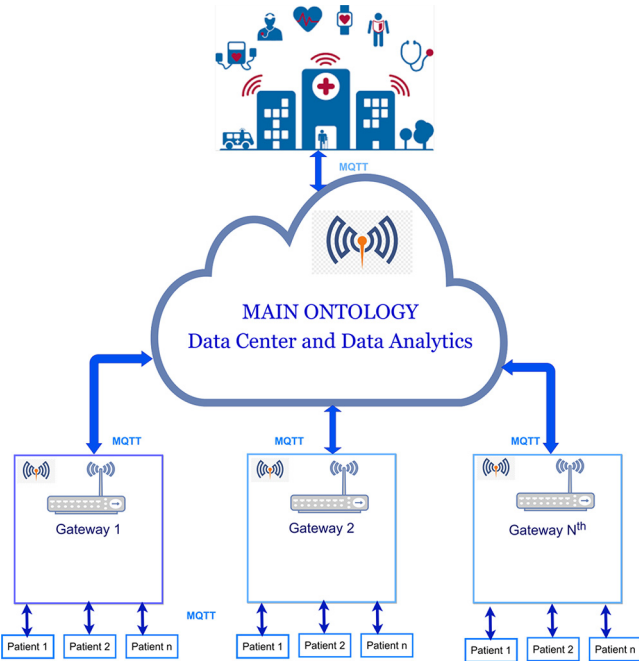


Figure 1.  
Block diagram

Class Name	Attributes	Ontology development approach
1. Patient	Patient ID	
2. Demographic Risks	Gateway ID	381
3. Behavioral Risks	Gender	
	Age	Table 1.
	Education	
4. Medical History	Smoker	Data set with fields
	Cigarettes/day	
	Physical activity	
	Healthy diet	
	Alcohol consumption	
	Stress level	
	BPMeds	
	Prevalent stroke	
	Prevalent hypertension	
	Diabetes	
5. Physical Examination	SysBP	
	DysBP	
	BMI	
	Heart rate	
	Chest pain	
	Total cholesterol	
	Glucose	
6. Prediction results	Using machine learning	

**Q.1: What is the gateway id patient1 (patient id)?**

```
SELECT? gatewayId WHERE {
    ?patient a cvd:Ptient.
    ?patientcvd:hasPatientID? patientId.
    ?patinetcvd:hasGatwayID? gatewayID.
    FILTER (?patientId = 1)
}
```

**Q.2: What are demographic details of patient (patientid)?**

```
SELECT? demographicRisksProperties WHERE {
    ?patient a cvd:Patient.
    ?patientcvd:hasDemographicRisks? demographicRisks.
    ?demographicRisksPropertiesrdfs:domain? demographicRisks.
}
```

**Q.3: What are behavioral details of patient (patientid)?**

```
SELECT? behavioralRisksProperties WHERE {
    ?patient a cvd:Patient.
    ?patientcvd:hasBehavioralRisks? behavioralRisks.
    ?behavioralRisksPropertiesrdfs:domain? behavioralRisks.
}
```

**Q.4: What is the medical history of patient (patientid)?**

```
SELECT? patientID? glucoseLevel? totalCholesterol? isDiabetePatient?
isHereditaryStatus? isPrevalentHperTension? isPreviouslyhadStroke?
isUnderBloodPressure
```

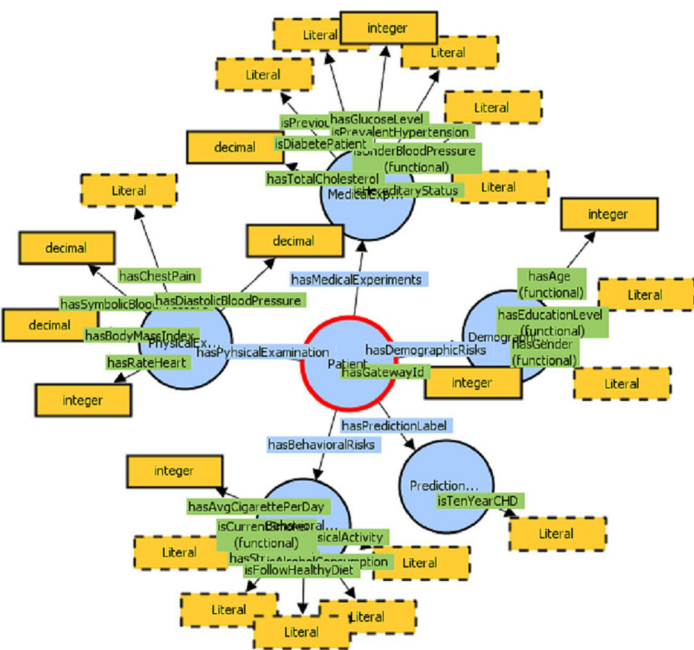


Figure 2.  
VoWL of the classes  
and relationships

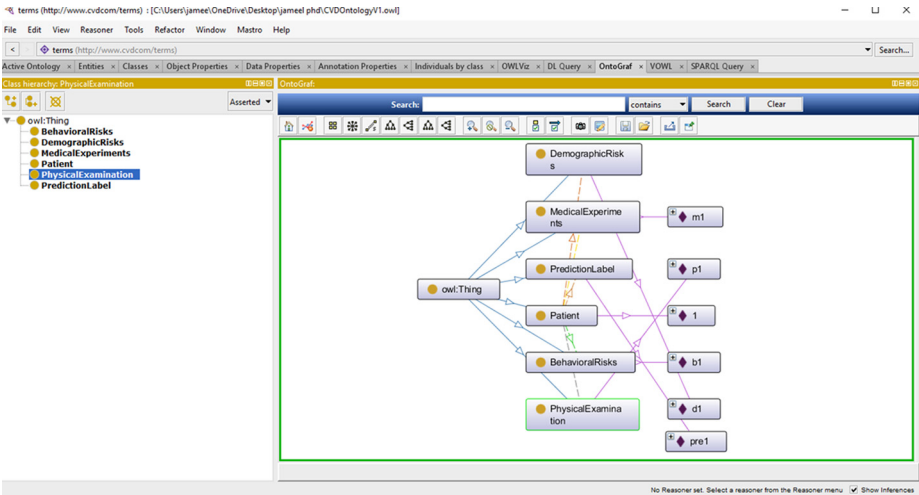


Figure 3.  
Ontograph of the  
classes

```

WHERE{
    ?patient      a cvd:      Patient.
    ?patient      cvd:hasPatientId      ?patientID.
    ?patient      cvd:hasMedicalExperiments      ?medical.
    ?medical      cvd:hasGlucoseLevel      ?glucoseLevel.
    ?medical      cvd:hasTotalCholesterol      ?totalCholesterol.
    ?medical      cvd:isDiabetePatient      ?isDiabetePatient.
    ?medial      cvd:isHereditaryStatus      ?isHereditaryStatus.
    ?medical      cvd:isPrevalentHypertension      ?isPrevalentHperTension.
    ?medical      cvd: isPreviouslyhadStroke      ?isPreviouslyhadStroke.
    ?medical      cvd:isUnderBloodPressure      ?isUnderBloodPressure.
}

```

**Q.5: What is the physical examination result of patient (patientid)?**

```

SELECT? patientID? bodyMassIdx? chestPain? diastolicBloodPressure? rateHeart?
symbolicBloodPressure

```

```

WHERE{
    ?patient      a cvd:      Patient.
    ?patient      cvd:hasPatientId      ?patientID.
    ?patient      cvd:hasPhysicalExamination      ?physical.
    ?physical     cvd:hasBodyMassIndex      ?bodyMassIdx.
    ?physical     cvd:hasChestPain      ?chestPain.
    ?physical     cvd:hasDiastolicBloodPressure      ?diastolicBloodPressure.
    ?physical     cvd:hasRateHeart      ?rateHeart.
    ?physical     cvd:hasSymbolicBloodPressure      ?symbolicBloodPressure.
}

```

**Q.6: What is the prediction result of patient (patientid)?**

```

SELECT? patientID? predictionLabelValue

```

```

WHERE{
    ?patient      a cvd:      Patient.
    ?patient      cvd:hasPatientId      ?patientID.
    ?patient      cvd:hasPredictionLabel      ?predictionLabel.
    ?predictionLabel      cvd:hasPredictionLabelValue      ?predictionLabelValue.
}

```

## 4. Experiments and results

The experiment is performed on the datasets collected from Kaggle and UCI repository. The data set is divided into five categories having different formats like Comma Separated Values (CSV), Java Script Object Notation (JSON) and Extensible Markup Language (XML). The data in heterogeneous nature is then pre-processed for removing unambiguity and null values. The pre-processed heterogeneous data is then applied to SDFizer engine for mapping to RDF suing RDF Mapping Language (RML). Configuration and mapping files are required for the mapping. The format of mapping is given as:

### 4.1 Mapping file

```

@prefix rr: <http://www.w3.org/ns/r2rml#>.
@prefix rml: <http://semweb.mmlab.be/ns/rml#>.
@prefix cvd: <http://cvd.com/terms#>.
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>.
@prefix ql: <http://semweb.mmlab.be/ns/ql#>.

```



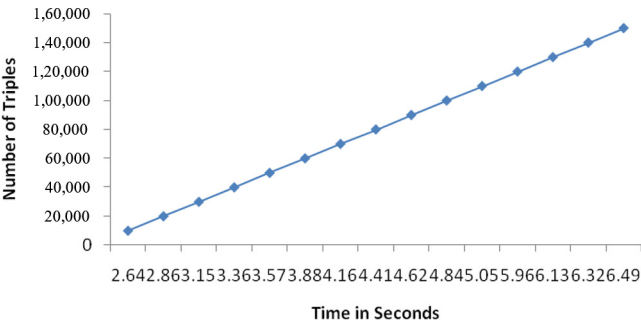
```
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .

<TripleMap1>
  rml:logicalSource[
    rml:source "C:/Users/jameel/Desktop/files/DemographicRisks.csv";
    rml:referenceFormulation ql:CSV
  ];
  rml:logicalSource [
    rml:source "C:/Users/Desktop/jameel/Desktop/files/BehavioralRisks.xml";
    rml:referenceFormulation ql:XML
  ];

<TripleMap2>
  a rr:triplesMap;
  rml:logicalSource [
    rml:source "C:/Users/Desktop/jameel/Desktop/files//MedicalExperiemnts.json";
```

**Table 2.**  
Description of  
attributes

Education	High school Diploma, College Higher education
BPMeds	Patient on blood pressure medications
Systolic Blood Pressure	The first number is the systolic blood pressure, which is measured as the heart pumps blood across your body. The diastolic pressure is what happens when the heart relaxes. The top or highest number (systolic) of blood pressure typically ranges from 90 to 250, and the bottom or minimum number (diastolic) usually ranges from 60 to 140. (diastolic) (Loomba <i>et al.</i> , 2012)
Diastolic Blood Pressure	The diastolic reading, also known as the bottom number, refers to the pressure in the arteries when the heart is at rest in between beats. This is when the heart receives oxygen and fills with blood. A diastolic blood pressure of less than 80 is considered normal. If your blood pressure is 90 or higher, you have high blood pressure (Loomba <i>et al.</i> , 2012)
Chest pain	Types of Pain in the chest (a) typical angina (b) atypical angina (c) non-anginal pain (d) asymptomatic



**Figure 4.**  
Conversion time



s	Smoker	Alcohol consumption	Prevalent hypertension	Under blood pressure	Diastolic blood pressure	Heart rate	Body mass index	Gender
<a href="http://cvd.com/terms/1">http://cvd.com/terms/1</a>	0	Non alcoholic	0	0	70	80	26.97	1
<a href="http://cvd.com/terms/2">http://cvd.com/terms/2</a>	0	Non alcoholic	0	0	81	95	28.73	0
<a href="http://cvd.com/terms/3">http://cvd.com/terms/3</a>	1	Occasionally	0	0	80	75	25.34	1
<a href="http://cvd.com/terms/4">http://cvd.com/terms/4</a>	1	Occasionally	1	0	95	65	28.58	0
<a href="http://cvd.com/terms/5">http://cvd.com/terms/5</a>	1	Non alcoholic	0	0	84	85	23.1	0
<a href="http://cvd.com/terms/6">http://cvd.com/terms/6</a>	0	Non alcoholic	1	0	110	77	30.3	0
<a href="http://cvd.com/terms/7">http://cvd.com/terms/7</a>	0	Non alcoholic	0	0	71	60	33.11	0
<a href="http://cvd.com/terms/8">http://cvd.com/terms/8</a>	1	Non alcoholic	0	0	71	79	21.68	0
<a href="http://cvd.com/terms/9">http://cvd.com/terms/9</a>	0	Non alcoholic	1	0	89	76	26.36	1
<a href="http://cvd.com/terms/10">http://cvd.com/terms/10</a>	1	Non alcoholic	1	0	107	93	23.61	1

**Table 3.**  
Output (retrieved  
information)

```

rml:referenceFormulation ql:JSON
];

rml:logicalSource [
  rml:source "C:/Users/Desktop/jameel/Desktop/files/physicalExamination.csv";
  rml:referenceFormulation ql:CSV
];

<TripleMap3>
  a rr:triplesMap;
  rml:logicalSource [
    rml:source "C:/Users/Desktop/jameel/Desktop/files/predictionLabel.csv";
    rml:referenceFormulation ql:CSV
  ];

<TripleMap4>
  a rr:triplesMap;
  rml:logicalSource [
    rml:source "C:/Users/Desktop/jameel/Desktop/files//gateway.csv";
    rml:referenceFormulation ql:CSV
  ];

```

The transformed data set is retrieved from the output file and uploaded over the graph database for information retrieval. Information is retrieved based upon the requirement of the applications. The transformed data set and GraphDB repository statements are shown as below. A 144,260 of total statements are generated with 144,134 explicit, 126 inferred and 1.0 of expansion ratio. Time taken to convert to rdf is shown in Table 2.

Results: In this work, the information pertaining to patients for diagnosis of cardiovascular diseases is required. Hence, the competency questions are needed to be framed as per the need of the application as per framed in the above section. Information is retrieved by using SPARQL queries and is considered as the output of this model as shown in Table 3 and Figure 5. In brief, by

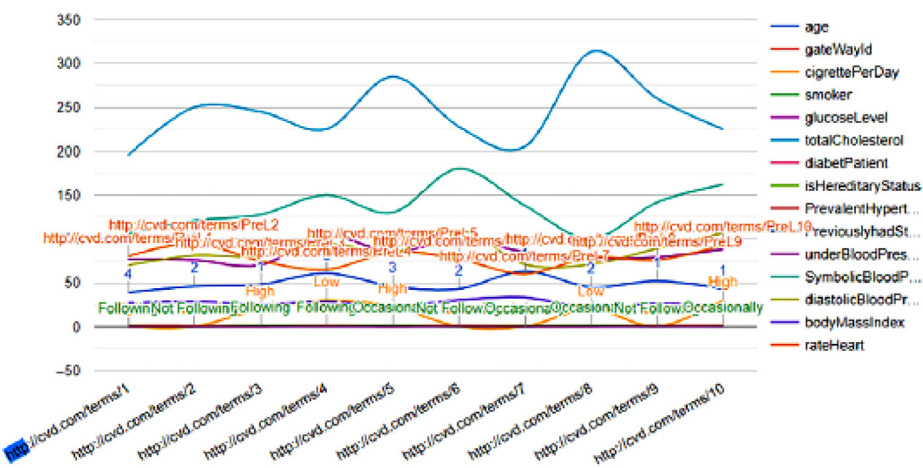


Figure 5.  
Output-information  
retrieved

using this model, doctors/specialists at any location can diagnose the patients by monitoring his/her health data. The health-care data of the patients is incremented continuously for regular monitoring and easily available to the experts in the literal and numerical forms (standardized as per the output of the medical testing instruments).

## 5. Conclusion

A comprehensive distributed, independent, separate and efficient information sources approach to critical and factual data contributes to one of the most dynamic states of interoperability in an IoT-based health-care system. The evolving system, semantic and structural heterogeneity of these potentially universal diverse data sources exacerbates this interoperability problem, dubbed semantic interoperability. In this paper, R2RML mapping approach is used for the transformation of raw data into RDF for the development of ontology. The ontology then is used for the realizing the IoT-based health-care system, where heterogeneous data needs semantic interoperability. The proposed approach enables us to collect the patient's data using user interface, biomedical sensors, mapped it to common format for shared understanding and ensures that the doctor can have the requisite information for diagnosis and continuous monitoring.

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### About the authors



Jameel Ahamed is a Student of Doctorate of Philosophy in Department of Computer Science and Engineering, National Institute of Technology, Srinagar, J&K. He is also working as an Assistant Professor in the Department of CS and IT, Maulana Azad National Urdu University, Hyderabad-Telangana, with over six years of experience in academic and research. His current research interests include internet of things, wireless sensor networks and computer networks. Jameel Ahamed is the corresponding author and can be contacted at: [jameel.shaad@gmail.com](mailto:jameel.shaad@gmail.com)



Roohie Naaz Mir is a Professor and the Head of the Department (HoD) in the Department of Computer Science and Engineering at the National Institute of Technology (NIT) Srinagar, India. She received BE (Hons) in electrical engineering from the University of Kashmir (India) in 1985, ME in computer science and engineering from the Indian Institute of Science (IISc), Bangalore (India) in 1990 and PhD from the University of Kashmir, (India) in 2005. She is a fellow in the Institution of Engineers (IEI) and the Institution of Electronics and Telecommunications Engineering (IETE), India, senior member of the Institute of

Electrical and Electronics Engineers (IEEE) and a member of the International Association of Computer Science and Information Technology (IACSIT) and the International Association of Engineers (IAENG). She is the author of many scientific publications in international journals and conferences. Her current research interests include reconfigurable computing and architecture, mobile and pervasive computing, security and routing in wireless ad hoc and sensor networks.



Dr Mohammad Ahsan Chishti has done his Doctor of Philosophy (PhD) from National Institute of Technology Srinagar (NIT Srinagar). He has completed Bachelor of Engineering (BE) and MS in Computer and Information Engineering (MSCIE) from International Islamic University Malaysia with specialization in Computer Networking. Before joining Central University of Kashmir as an Associate Professor, he was working as an Assistant Professor in the Department of Computer Science and Engineering, National Institute of Technology Srinagar, Hazratbal, J&K for more than 12 years. He has more than 70 research publications to his credit and

13 patents with two granted International Patents. His research area includes Internet of Things, Computer Networks, Next Generation Networks, MPLS and Technology Roadmapping. He is currently supervising a number of research scholars in his research group for the award of PhD degree and has served technical program committees and reviewer of many International conferences and journals.