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A semantic-enabled and context-aware monitoring system for the internet of medical things

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Abstract

The emergence of the Internet of Things (IoT) in the medical field has led to the massive deployment of a myriad of medical connected objects (MCOs). These MCOs are being developed and implemented for remote healthcare monitoring purposes including elderly patients with chronic diseases, pregnant women, and patients with disabilities. Accordingly, different associated challenges are emerging and include the heterogeneity of the gathered health data from these MCOs with ever-changing contexts. These contexts are relative to the continuous change of constraints and requirements of the MCOs deployment (time, location, state). Other contexts are related to the patient (medical record, state, age, sex, etc.) that should be taken into account to ensure a more precise and appropriate treatment of the patient. These challenges are difficult to address due to the absence of a reference model for describing the health data and their sources and linking these data with their contexts. This article addresses this problem and introduces a semantic-based context-aware system (IoT Medicare system) for patient monitoring with MCOs. This system is based on a core domain ontology (HealthIoT-O), that is, designed to describe the semantic of heterogeneous MCOs and their data. Moreover, an efficient interpretation and management of this knowledge in diverse contexts are ensured through SWRL rules such as the verification of the proper functioning of the MCOs and the analysis of the health data for diagnosis and treatment purposes. A case study of gestational diabetes disease management is proposed to evaluate the effectiveness of the implemented IoT Medicare system. An evaluation phase is provided and focuses on the quality of the elaborated semantic model and the performance of the system.

KEYWORDS

context-awareness, medical connected objects, ontology, patient monitoring

1 | INTRODUCTION

It has been revealed that IoT enables seamless communication between diverse devices and objects and helps people to interact continuously with them to establish a large connected network. The IoT is widely applied especially in the healthcare domain. According to Baker, Xiang, and Atkinson (2017) and Cai et al. (2014) medical care and health care stand as one of the most attractive application areas for the IoT.

Referring to the association of important R&D direction, the IoT with the medical sector applications gave birth to the Internet of Medical Things (IoMT).[1] According to Gatouillat, Badr, Massot, and Sejdić (2018), IoMT designates the interconnection of communication-enabled medical-grade devices and their integration to wider-scale health networks in order to improve patients' health. This harmonious relationship paves the way of various intelligent services such as diagnoses and prevention of illness, decision support for appropriate treatment for patients, and remote patient monitoring (Islam, Kwak, Kabir, Hossain, & Kwak, 2015). Moreover, this use of connected objects makes the disease identification easier since its appearance and through its evolution. Therefore, this reveals that IoMT changes the medical field from a reactive and fragmented, that is a hospital and disease-centred, to a preventive and interoperable domain that mainly focuses on the patient's well-being and quality of life. IoMT can be utilized for prospective studies that require a regular monitoring, either frequent or momentary, on a large scale beyond the capacity of conventional logistics necessitating the physical reception of individuals on a particular site (hospital, laboratory). Moreover, in the actual period when the COVID-19 originated in China has swept the globe, healthcare professionals are advised to apply the IoT in order to monitor confirmed patients with COVID-19 and reduce the spread of this virus by not only preventing patients from circulating but also allowing immunized patients to circulate in an ordinary way. Furthermore, in the lock-down period, IoT monitor patients and even healthy people in order to manage authorizations and to determine the rate at which a company has been reached in the case of a pandemic.

In this way, several medical connected objects (MCOs) are developed and deployed such as Zio Patch that measures heart rate and electrocardiogram (ECG) (Tung, Su, Turakhia, & Lansberg, 2015). Smart wearable devices are proposed by Novartis and Google to observe the blood glucose level (Senior, 2014), Withings is a wireless blood pressure monitor developed by Nokia (Topouchian et al., 2014), mobile devices to monitor the progression and treatment of Parkinson disease[2] is an ongoing project between Pfizer and IBM, and so on. Patients use these MCOs to monitor their measurements (temperature, blood pressure, etc.). Through the communication technologies, the MCOs are enabled to exchange the detected measurements with the doctors' medical object for helping them for continuous and remote monitoring of their patients. After the diagnosis of the received measures, the doctors can share the result with the patient or with his family. Accordingly, since these MCOs are designed by different manufacturers (Google, IBM, Nokia, etc.), they are heterogeneous in terms of deployment contexts, computing capabilities, and communication protocols. Accordingly, the exchanged information is heterogeneous in formats and units and does not have the same coding format. In this context, ensuring the semantic interoperability between these heterogeneous MCOs becomes difficult.

To deal with this challenge a reference model that defines all of the MCOs, their data, and their formats is required to ensure interoperable MCOs. This model should define the MCOs, in terms of characteristics, capabilities, deployment contexts, measurements and so on. It should also contain knowledge about the observed patient such as symptoms, treatments, events, risks.

To this end, Semantic Web Technologies (Berners-Lee, Hendler, & Lassila, 2001) and especially ontologies are a promising solution. Ontology allows representing knowledge about the domain in a well-structured and comprehensive description. According to Studer, Benjamins, and Fensel (1998) an ontology is a formal, explicit specification of a shared conceptualization of a domain of interest. Ontology explicitly defines the IoT domain and the healthcare domain knowledge and their relationship.

On the other hand, it is primordial to link them with their various contexts in order to ensure their appropriate and correct management. In our work, we focus on two types of contexts: the patient' context and the employed device' context. For the first, the patient health status context can be considered in order to decide the adequate diagnosis and treatment, for example, the blood glucose level of a pregnant woman is different from that of a non-pregnant woman. In addition, the time context is used to define the required time to monitor the patient and to analyse her/his health data. Moreover, we can also focus on the location context to determine the place of the patient and make a suitable suggestion. Regarding the employed device context, it is required to verify and diagnose its state in order to be sure about the reliability of the gathered data and to be able to easily repair it in case of damage.

From this viewpoint, context-awareness computing (Perera, Zaslavsky, Christen, Compton, & Georgakopoulos, 2013) is an important research topic that should be taken into account in the IoMT field. It allows the interpretation of the patient's health state, and avoids misdiagnosis and errors due to the misunderstanding of the patient state by assigning the clinical signs to their contexts. In addition, it helps to accelerate the diagnostic time.

Hence, the present article exploits Semantic Web Technology (SWT) (Berners-Lee et al., 2001) and context-awareness computing (Yürür et al., 2016) and suggests a semantic-based context-aware patient monitoring approach. This approach is composed by four main phases: the data collection and preprocessing phase, the semantic modelling phase, the analysis phase, and the implementation phase.

The main novelties of this article lie in the following aspects:

- Proposing a unified model (HealthIoT ontology) of the obtained data (technical and health data) to be efficiently used by heterogeneous healthcare IoT-based systems. This model contains knowledge about the IoT and the healthcare domain and the relationships between them. At this level, we aim to extend our previous work on HealthIoT in Rhayem, Mhiri, and Gargouri (2017) and Rhayem, Mhiri, Salah, and Gargouri (2017), where we proposed a HealthIoT ontology, by implementing new concepts related to the contexts of the medical devices and patients, respectively.
- Assisting doctors in the exploitation of the collected data by the technique of automated reasoning based on SWT. We consider here the use-case of gestational diabetes context and we develop the related analysis rules that are based on the generic ontology (HealthIoT).
- Verifying and configuring the proper functioning of the employed MCO by exploiting its employment context information, in order to guarantee the certainty of the detected data.

- Developing a clinical decision support system (IoT Medicare system) to implement the proposed knowledge base based on SWT technologies (SPARQL, Jena API) for automatic selection of clinical and configuration services. Thereby, at this level, we define end-users interfaces taking into account the requirements of three users (patient, doctor, administrator).
- Evaluating the semantic quality of the proposed knowledge base (HealthIoT ontology) based on the OQuaRE framework (Duque-Ramos et al., 2014). In addition, we aim to assess the performance of our system in terms of precision, recall, f-measure and response time.

The rest of this article is organized as follows: Section 2 describes our proposed use case about gestational diabetes monitoring. Section 3 provides an overview about IoMT-systems and the semantic representation in this domain. Section 4 highlights our semantic-based context-aware architecture that is composed of four main phases: the data collection and preprocessing, the semantic modelling, the analysis, and the implementation phases. These phases are described in Sections 5–8, respectively. The evaluation of our approach is illustrated in Section 9 based on technical and functional levels and a comparison with existing approaches. Finally, Section 10 draws our conclusion and suggests future perspectives.

2 | USE CASE: GESTATIONAL DIABETES MONITORING

Gestational Diabetes is a disease that should be continuously monitored in order to follow its evolution and make an adequate decision according to its behaviour. In this context, a pregnant woman needs to communicate and to share her glucose level with the medical staff, receive notification from them, accelerate their intervention in difficult cases. On the other hand, medical staff needs easy access to the patient's data to interpret them and suggest the appropriate treatment. To alleviate these challenges, the medical sector adopts IoT technology. Thereby, various researchers, Cappon, Acciaroli, Vettoretti, Facchinetti, and Sparacino (2017), Kim, Campbell, and Wang (2018), and Wang and Lee (2015) have implemented diverse MCOs to monitor the state of a pregnant woman. These MCOs contains diverse sensors to detect the patient's blood glucose, heartbeat, blood pressure, etc. These objects are heterogeneous in terms of deployment contexts, computing capabilities, and communication protocols. They generate a huge amount of heterogeneous and ambiguous data that describe various cases. The health data represent patients' states while technical data shows the states of medical objects. In fact, both doctors and patients use connected objects that are designed by different manufacturers (Google, IBM, Nokia, etc.). Accordingly, the generated data has different coding formats leading to a complex data exchange task. Moreover, this amount of data, including semantic heterogeneity (synonymy, antonymy, polysemy, etc.), keeps growing. This numeric information can be badly understood and exploited by other systems and devices. For example, when sensed blood glucose value reaches 200, its responsible sensor sends this data to the doctor's object (smartphone). This later should have further details to understand that this value refers to the blood glucose level of an ordinary diabetic patient or a pregnant woman that equals to 200 mg/dL, which exceeds the threshold and requires an alert triggering. Accordingly, this received data should be presented in a unified model, easy to be processed and exploited by the doctor's equipment or object. This model should define contextual information reflecting the context of the sensed data (source, the type of measurement, unit, patients personal information, time of detection, location, etc.) in order to address accurate alerts for doctors and propose the adequate actions that should be taken depending on the patient state. Also, a doctor is able to validate or to change these actions before sending any decision to the patient's object (smartphone).

In the same context, technical data is incredibly important to configure and manage the state of the used object in order to repair any functional breakup.

Assuming that the MCO of a pregnant woman fails (discharged battery, ending lifetime, broken connection), the medical staff encounters a big challenge to remotely monitor their patient. In this case, these devices should be replaced with another of the same type (e.g. blood glucose sensor should not be replaced with a temperature sensor). Hence, the monitoring task will be assigned to the new available object to perform this new task. Indeed, this object should be connected to the internet. Therefore, in indoor environments, the object can be connected to the home gateway as the patient stays at home. In outdoor environments, however, the object can be connected to the internet via the 4G wireless network. In this respect, verifying the connectivity and availability of this object is a vital step before assigning the new task. Besides, testing the MCOs mobility can determine the location of the pregnant woman and consequently facilitate the intervention of healthcare professionals in any emergency case. As a result, treating information about the crossed trajectory is vital to track the MCO mobility. Once the state of the object is reliable, doctors are able to treat and diagnose patients' states. First, the validity of the obtained blood glucose level for possible treatment should be checked. Diagnosing the blood glucose level during a predefined time interval helps avoid adverse events, like fainting and dyspnea. Second, doctors will diagnose blood glucose values in pregnancy. Thus, they are permanently diagnosed during the second and third semesters of pregnancy. These values can be recognized based on two different glucose tests according to the Americain of Diabetes (ADA) Association et al. (2018). The Fasting Plasma Glucose (FPG) should be between 92 mg/dL (5.1 mmol/L) and 126 mg/dL (7.0 mmoL/L). The Oral Glucose Tolerance Test (OGTT) is ≥180 mg/dL (10.0 mmol/L) after 1 hour and ≥153 mg/dL (8.5 mmol/L) after 2 hours. Third, the diagnostic test results and medical records of a pregnant woman (age, weight, historical diseases, tests) help doctors estimate possible health complications and the most dangerous risks. In fact, according to the World Health Organization (2016), uncontrolled diabetes during pregnancy cause hazardous effects on both the mother and child, such as the risk of foetal loss, congenital malformations, and stillbirth. Diabetes treatment in pregnancy depends on the blood glucose level. In fact, at a medium level, doctors can resort to just a dietary plan. However, at a high glucose level, doctors suggest a medication therapy (e.g. metformin three times per day during or after meals, insulin injections) that will be taken only during the pregnancy period. After that, doctors send notifications of adequate treatments for patients or their families through alarms sent by doctors' connected objects. In an emergency case, when symptoms of foetal loss appeared, doctors' connected objects should forward an emergency alert to the hospital in order to urgently send an ambulance. To treat these cases, it is essential to develop an application in order to assist users to control and configure MCOs regardless of their location (e.g. a doctor at home can control the remotely connected medical devices of his patients to verify their reliability and trust; he can send/receive notifications to/from them). Besides, this application will enable users to share knowledge about the state of patients and the appropriate treatments, via their objects. In this regard, the main goal of this work is to propose a semantic-enabled context-aware approach that consists in:

- Defining a semantic representation of medical objects with their data and contexts to resolve the semantic heterogeneity problem.
- Facilitating the diagnosis of the health states of pregnant women based on the semantic model by taking into account myriad contexts such as, age, symptoms, hypertension.
- Ensuring the good functioning of the employed medical objects to guarantee sustainable and effective pregnant women's monitoring.
- Facilitating the interaction between doctors and users through the development of a semantic-based patient monitoring system. This system fulfils the following users' requirements:
  - Patient requirements: Patients (pregnant women) can continuously control their states by consulting the collected measurements. Each patient is also willing to receive and verify any notification sent by his/her doctor.
  - Doctor requirements: The doctor is able to monitor a group of patients by analysing their measurements in a given context; they can remotely consult the proposed diagnosis report by our system and to make a change if necessary. In addition, doctors can communicate and send the appropriate diagnosis and results for patients through the triggering of alarms.
  - System administrator requirements: The administrator can control the proper functioning of the MCOs used by the doctors and their patients. He is able to send notifications for users if he encounters a problem in the object and to automatically resolve it.

3 | LITERATURE REVIEW

This section is divided into two sub-sections. In the first one, we give an overview of the most recent applications of the IoT in the healthcare domain. In the second sub-section, we will focus on the semantic representation approaches in this domain. First, we study the proposed approaches in the IoT in general. Second, we interest in approaches that define the semantics of IoT-based healthcare systems. After that, we underline the main contributions of our work.

3.1 | IoT-enabled smart healthcare

The continuous need of a low-cost remote monitoring system for elderly patients with chronic diseases has encouraged software developers to adopt IoT technologies in the healthcare field. The works of Jayatilleka and Halgamuge (2020) and Mishra and Rasool (2019) have overviewed the recently developed IoT devices that guarantee a reliable and secure patient monitoring and treatment delivery in the healthcare domain.

This adoption shows important and adequate results for improving the quality of healthcare services in smart environments (Meigal, Korzun, Gerasimova-Meigal, Borodin, & Zavyalova, 2019; Turcu & Turcu, 2019).

Diverse applications have been developed for diabetes (Puri, Kumar, Le, Jagdev, & Sachdeva, 2020), heart disease (Khan, 2020), hypertension (Sood & Mahajan, 2018), Alzheimer (Varatharajan, Manogaran, Priyan, & Sundarasekar, 2018), epileptical patient monitoring (Gupta, Chakraborty, & Gupta, 2019), and so on.

In what follows, some recent IoT-based monitoring systems are detailed.

Diabetes monitoring: Chatterjee et al. (2018) implemented an IoT-based home monitoring system for diabetic patients. This approach aims at monitoring the daily activities of these patients to trigger alerts concerning their dietary behaviour when necessary. Puri et al. (2020) have developed an IoT-based diabetes monitoring system that is capable of detecting and analysing blood sugar, body temperature, and other environmental parameters (temperature, humidity). This system encrypts data to ensure its secure transmission, analysis and storage in the cloud.

Heart rate monitoring: Liu, Chen, and Wang (2018) have applied a medical IoT system based on wireless sensor networks for ECG monitoring. This system detects and transmits physiological parameters and image data to the base station. This data can be easily accessed and analysed by medical professionals through their PDA and computers to ensure a timely treatment in an abnormal state. Therefore, Khan (2020) have developed and IoT framework for heart disease prediction. They used a smartwatch and a heart monitor device to monitor blood pressure and electrocardiogram measurement. These measurements were then analysed through the modified deep convolutional neural network (MDCNN) for heart disease prediction. Santos, Trujillo, Portilla, and Rosales (2019) have set forth an e-health system for heart rate monitor in Ecuador. This system supports continuous care and suggests primary diagnostic assistance service of heart disease. It bases its operation on video processing algorithms, which are collected through web cam and mobile device that communicate with a central data base station via WAN network.

Hypertension monitoring: Sood and Mahajan (2018) proposed an IoT-fog health monitoring system to monitor the blood pressure level to predict real-time hypertension event. In addition, this system focused on predicting health complications and risks based on several machine learning algorithms and alerts generation.

CoronaVirus monitoring: With the CoronaVirus outbreak, which first appeared in China, several researchers are working on IoT exploitation to be able to control and prevent this pandemic. Bai et al. (2020) have offered a diagnosis and treatment system for COVID-19 based on the IoT to overcome the potential problems of the lock-down. The latter leads to an increased risk for chronic diseases since patients cannot make the classical periodical blood analysis. For this reason, the main asset of this system is to remotely monitor outpatients in the containment zone and ensure a fast and reliable intervention if necessary. It helps doctors, at the early stages of this disease, guarantee timely treatment of confirmed cases and facilitate the interaction between experts and managers to deeply investigate or expand the diagnosis and treatment of COVID-19 and to help health authorities to handle individually the lock-down in order to limit the virus propagation, by allowing immunized persons to circulate. Both a smartphone and a PC, key components of this system, are used for patient monitoring and cloud computing for data storage, communication, and transmission technologies.

To ensure reliable and efficient health data analysis and interpretation, an IoT-based system should understand the contextual information of the obtained measurement. Wherefore in order to tackle the challenges of heterogeneous data fusion and context-awareness query processing in the IoT health domain, Baloch, Shaikh, and Unar (2018) have proposed a context-aware data fusion in the IoMT domain. This approach is composed of context acquisition, data fusion, and inference and reasoning steps.

Aborokbah, Al-Mutairi, Sangaiah, and Samuel (2018) have also introduced a support vector machine-based context-aware decision support system for healthcare service delivery in smart cities. This system interpreted the patient's clinical state based on multiple vital signs (heart rate, temperature, blood pressure) for early prediction of heart failure risks. Furthermore, it could provide real-time analysis of physiological data to continuously determine the state of the patient and provide optimal health care services.

Barbosa, Tavares, Cardoso, Alves, and Martini (2018) have offered a context-aware system to assist wheelchair users. It recommends accessible resources in indoor and outdoor environments during their displacement process based on various contexts, like location, time, users' identity, etc.

To ensure the security of health data transmission between sensors, Arfaoui, Kribeche, and Senouci (2019) have adopted a context-aware and lightweight anonymous authentication scheme for Wearable Body Area Networks (WBAN) applications in emergency and normal situations. Their proposed scheme provides selective anonymous authentication between nodes in WBAN while taking into account the dynamic context changes (the battery level of sensors, memory capacity, etc.).

In Table 1, we present a comparison of the above-mentioned works, related to the IoT-based healthcare monitoring system. This comparison is based on diverse criteria to give a general overview of the main properties of IoT-based systems in the healthcare domain. The used devices criterion aims to list the different deployed IoT devices. The communication technology identifies the types of the used technologies to connect the IoT devices. The application criterion determines the application domain of the developed system. The context type criterion allows identifying the modelled and treated contexts in the IoMT. The reasoning methods criterion identifies the principal used methods and techniques for data interpretation. The tools criterion verifies if the proposed works have developed and evaluated their approaches on a real use case. According to this comparative table diverse types of IoT devices are used in the healthcare domain and connected to various communication technologies. In addition, they are based on diverse techniques for data interpretation and management tasks. However, only some works put special focus on context-awareness in the internet of medical things. Several contexts are defined in these works, such as location, time, patient's state, device's requirement. In fact, contexts related to the device's functioning are only considered by Arfaoui et al. (2019), who directed their attention to ensure safe operation of IoT devices during data collection and transmission.

However, these approaches have not considered using ontologies to ensure the semantic interoperability in the IoMT and to model and manage contexts in this domain. This was our main objective in this article. From this regard, much attention has been given to the related works presented in Section 3.2.

3.2 | Semantic representation in the IoMT domain

In this section, we will focus on the semantic representation of the IoMT knowledge. Accordingly, it is crucial to study at first the proposed approaches in the IoT field in general and then on the IoMT.

TABLE 1 A comparison of recent monitoring systems for the IoMT

References	IoT devices	Communication technology	Context type	Reasoning methods	Tools
Chatterjee et al. (2018)	Ambient sensors (switch, sensor for activity), IoT devices (BG monitor), ody wearable devices	WSN	×	RNN	Yes
Liu et al. (2018)	ECG sensor	WSN	×	Image processing techniques	Yes
Santos et al. (2019)	Web cam and mobile device	WAN	×	×	Yes
Chatterjee et al. (2018)	Health sensor (blood pressure sensor, heart rate, etc.), accelerometer, bio sensor, RFID tag, etc.	×	Multiple vital signs (blood pressure, heart rate, respiratory rate), patient's activity	ANN	Yes
Baloch et al. (2018)	IoT sensors	×	Location, environment	×	No
Aborokbah et al. (2018)	×	×	Considering multiple vital signs	SVM	Yes
Barbosa et al. (2018)	RFID cards	RS-232, Bluetooth	Indoor, outdoor locations, time		Yes
Arfaoui et al. (2019)	WBAN	WSN	Device contexts (battery level, memory capacity, etc.)	Mathematic-based reasoning	Yes
Puri et al. (2020)	Glucose sensor, trans-conductance amplifier, and micro-controller	WiFi	×	If-Then rules	Yes
Khan (2020)	Smart watch and heart monitor device	LoRa technology	×	MDCNN	Yes
Bai et al. (2020)	Sensors for heart rate, temperature, respiratory rate, etc.	5G technology	×	×	Yes

Abbreviations: ANN, artificial neural network; ECG, electrocardiogram; IoMT, Internet of Medical Things; IoT, Internet of Things; MDCNN, modified deep convolutional neural network; RNN, replicator neural network; SVM, support vector machine; WAN, wide area network; WBAN, wearable body area network; WSN, wireless sensor networks.

3.2.1 | IoT ontologies

Over the last few years, diverse ontologies are suggested in the IoT field. Some of them are described below. However, a deepen investigation about SWT in the IoT was proposed in Rhayem, Mhiri, and Gargouri (2020).

The most referenced work was suggested by Compton et al. (2012), who put forward a Semantic Sensor Network (SSN) ontology. It describes sensors in terms of capabilities, measurement processes, observations and deployments in order to define the semantic interoperability of physical sensor networks. Its core concepts are sensors and their properties, observations, systems, measuring capabilities, operational and survival restrictions, and deployments.

The SSN ontology is then extended to represent multimedia sensor by Angsuchotmetee, Chbeir, and Cardinale (2018).

Nonetheless, the IoT domain does not only include sensors, but also other concepts that have to be addressed, namely the actuator, the physical object. The former is responsible for generating actions while the latter is connected to the internet and integrates sensors, actuators, devices, among others. For that reason, diverse approaches were realized in the last few years in order to represent the IoT domain knowledge. Among these approaches, we will present the most common and cited ones.

To achieve this purpose, Bauer et al. (2013) have defined an IoT-A architecture in IoT. This model defines the core concepts of this domain, such as physical entity, virtual entity, sensor, tag, actuator, service, and user.

In addition, to represent the semantics of actuators and their capabilities and roles, the SOSA ontology was suggested by Janowicz, Haller, Cox, Le Phuoc, and Lefrancois (2018). It was proposed by both the joint group World Wide Web Consortium (W3C) and the Open Geospatial Consortium (OGC) in order to elucidate the interactions between sensors, observations, actuators, and sample concepts.

Therefore, in the context of the ADREAM project, Seydoux, Drira, Hernandez, and Monteil (2016) proposed a modular ontology (IoT-O)[3] to ensure a semantic interoperability between IoT components. IoT-O contains several modules, like sensing, actuation, life cycle, service and energy modules.

Ma, Wang, and Chu (2014) set forth a semantic information model for IoT applications, known as OntoIoT ontology. In fact, the latter describes (a) real word entities (objects being monitored, sensor devices, and network infrastructure), (b) spatial and temporal dimensions, (c) the captured (dynamic and static) data, (d) services including applications (e.g. in the areas of healthcare or traffic), functions, and interfaces.

In the context of both the EU FP7 FIWARE project[4] and the EU H2020 FIESTA-IoT project[5] Bermudez-Edo, Elsaleh, Barnaghi, and Taylor (2016) developed an IoT-lite ontology with the aim of describing IoT concepts in three different classes: Objects, systems or resources, and services. This ontology is a lightweight instantiation of the SSN ontology.

In the same context, Agarwal et al. (2016) proposed a unified ontology, which reuses a number of core concepts from several ontologies, such as Semantic Sensor Network (SSN), M3-lite, WGS84, IoT-lite, Time, and DUL in the IoT domain.

We present a comparative table, of the different approaches mentioned above, that shows the use of ontologies to resolve the semantic heterogeneity in the IoT domain. The comparison is based on the following criteria:

- IoT concepts: This criterion identifies the main proposed concepts of the IoT.
- Ontologies reuse: within this criterion, we aim to identify if the proposed ontology reuses concepts from a previous one and to check whether these ontologies are built from scratch.
- Contextual information: This criterion determines the presented contexts in the proposed ontologies. We have identified five major contexts that are important in the IoT domain, namely time, location, inter-connectivity, trajectory and objects' requirements.
- Reasoning: This criterion verifies whether the proposed approaches suggested rules for either device management or data management.

According to Table 2, we notice that most of these approaches take advantage of reusing existing ontologies instead of building new ones from scratch. SSN was one of the most referenced ontologies in these approaches as it presents a pivotal component for each IoT-based system. Furthermore, the main modelling contexts in these works are time and location with little emphasis on inter-connectivity, requirement, and trajectory contexts. Concerning the reasoning phase, none of these approaches was interested in managing the state of the employed object, such as checking its availability, connectivity, and task allocation. Therefore, reasoning about the obtained data from IoT devices was addressed by only some works, like Angsuchotmetee et al. (2018), Ma et al. (2014), and Seydoux et al. (2016).

The next sub-section will be devoted to the semantic representation of the adoption of IoT in the healthcare domain.

3.2.2 | Semantic-based IoMT-systems

Ensuring the semantic interoperability in the IoT and the healthcare fields gave rise to diverse research issues. Therefore, numerous ontologies are available in the medical domain.

TABLE 2 Comparison of semantic-IoT related works

Reference	IoT concepts	Ontologies reuse	Contextual information	Reasoning: Device management	Reasoning: Data management
Compton et al. (2012)	Sensors and their observations	SemSOS, Ontonym-Sensor, CESN, O&M	Time, location	×	×
Bauer et al. (2013)	Physical entity, sensor, actuator, RFID tag, user, service, network	SSN	Connectivity	×	×
Ma et al. (2014)	Object, device (sensor, actuator, RFID), network	×	Time, location	×	√
Seydoux et al. (2016)	Sensor, actuator, observation, actuation, service, power-consumption	SSN, DUL, PowerOnt	Time, device	×	√
Bermudez-Edo et al. (2016)	Sensor, actuator, RFID tag, location	SSN, Geoname, SAO	Location	×	×
Agarwal et al. (2016)	Sensor, actuator, RFID tag, physical entity, virtual entity, service, location, time	SSN, IoT-lite, M3, Time	Time, location	×	×
Angsuchotmetee et al. (2018)	Multimedia sensor, their data and their properties	SSN, SOSA, MA-Ont	Time, location, trajectory	×	√
Janowicz et al. (2018)	Sensors, observations, actuators, actuation	SSN	Time, location	×	×

Abbreviations: IoT, Internet of Things; SSN, Semantic Sensor Network.

The Open Biomedical and Biological Ontology (OBO), according to Smith et al. (2007), was developed in the field of biomedical informatics. It is based on the upper-level ontology Basic Formal Ontology (BFO).

UFO (ECG) ontology (Gonçalves, Zamborlini, & Guizzardi, 2009) is an ontology for the electrocardiogram diagnosis based on the UFO ontology. This model proposed a unified model of the ECG data.

Therefore, several researchers have addressed the semantic interoperability issue in the IoMT domain. Alirezaie et al. (2017) came up with an ontology-based system called '*E-care@home*'. It consists of three different parts, namely E-care@home database, IoT devices, and software and protocols. This Smart Home Ontology is defined to describe and interpret the heterogeneous sensor data.

The work achieved by Chen, Jin, Goh, Li, and Wei (2016a), the authors proposed an anti-hypertensive Drugs Personalized Recommendation Service Context Ontology (HyRCO). This model is divided into seven core classes, namely: *User*, *Activity*, *Environment*, *Device*, *Service*, *Location* and *Anti-hypertensive*. It defines context rules to provide a drug recommendation service for the hypertension disease based on SWRL language. Recently, the SAREF ontology was extended for the healthcare domain (Moreira, Pires, van Sinderen, & Daniele 2018) and specifically for monitoring electrocardiogram (ECG) data.

Esposito et al. (2018) have implemented an ontology-based context-aware architecture for personal monitoring that can be deployed in mobile devices. This architecture has addressed the challenge of self-configuring IoT devices, contextual information extraction related to patients for later analysis and interpretation, the fusion of contextual information with sensor data in order to detect suspicious anomalies and supply adequate alerts. This architecture comprises four distinct layers, namely the sensing layer, the perceptual layer, the reasoning layer and the actuating layer.

El-Sappagh, Ali, Hendawi, Jang, and Kwak (2019) have offered a semantic-based system to monitor type 1 diabetes mellitus based on FASTO ontology. This ontology combines patient data from heterogeneous sources by integrating the SSN ontology, the fast healthcare interoperability resources (FHIR), the BFO, and the clinical practice guidelines.

Rubí and Gondim (2020) have developed an interoperable IoMT platform by the alignment between the SSN ontology and the Electronic Health Record (EHR). This platform is based on the M2M architecture that enables communication between the different components of the IoT platform. Table 3 displays a comparison of the developed ontologies in the IoMT domain based on some criteria. First, the IoT devices criterion determines the modelled IoT devices in the proposed ontologies. Second, the interoperability criterion verifies whether the proposed ontology was either developed from scratch or based on reusing other ontologies. Third, the context-aware criterion demonstrates if the ontology contains concepts related to both the deployed medical context, such as time, location, and trajectory, and patients' contextual information, like diseases, symptoms, historic data. Fourth, the reasoning criterion determines whether the proposed works were interested in not only diagnosing the patients' state, anticipating possible risks for prevention purposes, and proposing treatment but also checking the connected objects' states. Finally, the users' criterion aims to identify to whom the proposed system was addressed.

TABLE 3 Criteria and health care ontologies comparison

References	IoT devices	Interoperability	Context-aware	Reasoning goals	Users
Chen, Jin, et al. (2016)	Sensors (temperature sensor, blood pressure sensor, respiratory rate sensor)	No	Patient	Treatment for hypertension disease	Patient
Alirezaie et al. (2017)	Home sensors (luminosity, motion, pressure, etc.)	SSN	Time, location, Patient's activity	Activity recognition	Patient
Moreira et al. (2018)	Electrocardiogram sensors	SSN/SOSA, UFO ECG	No	No	Patient
Esposito et al. (2018)	Sensors	No	Patient's activity	Diagnosis	Doctor and patient
El-Sappagh et al. (2019)	Wearable body sensors	SSN, BFO	Patient	Diabetes type 1 treatment	Patient
Rubí and Gondim (2020)	Sensors	SSN	No	No	Doctor

Abbreviations: BFO, Basic Formal Ontology; IoT, Internet of Things; SSN, Semantic Sensor Network.

3.2.3 | Synthesis

After examining Table 3, we can still recognize some shortcomings in applying SWT in IoMT, as described below.

- None of the aforementioned works proposed an ontology that covers the essential concepts in both the IoT and Healthcare domains. The majority of the suggested approaches in the healthcare field ignored reusing the already defined IoT models. That is to say, they limited health data source description to only one sensor concept.
- Little attention was paid to the semantic relationships between IoT and healthcare components that can provide a comprehensive model to analyse health data gathered from IoT devices.
- The semantic context modelling is limited to time, location and users in the almost of approaches. It does not represent a specific context (e.g. capability, network, trajectory) for MCOs that affects their functioning. In addition, health care contexts were not considered in these approaches.
- The reasoning task is conceived to analyse the patient's health care state in a simple case. Researchers have not treated contexts in a detailed way. Additionally, to the best of our knowledge, none of these approaches have been interested in managing and interpreting the states of medical connected devices.
- Except for the study in Chen, Zhou, and Guo (2016), all the proposals do not take into account the whole diagnosis process which starts by detecting health data from heterogeneous sources followed by analysing the occurring event, then, anticipating risks and finally suggesting the suitable service in order to provide real-time notifications to patients.

From this perspective, our purpose was to address these problems. First, in order to increase the interoperability of our ontology, we reused some concepts extracted from diverse IoT ontologies, such as SSN, IoT-O, and IoT-lite. Second, diverse contexts were presented in our model that deals with the functioning of the used objects and the patients' states. Third, in the reasoning step, we focused on the remote monitoring of both medical objects and patients. To this end, we put forward and emphasized the M-E-R-T-A process which started by analysing the obtained data with a special emphasis on other factors (symptoms, historical diagnosis, age, sex), predicting the potential health risks and finished with the treatment proposition.

4 | SEMANTIC-BASED CONTEXT-AWARE APPROACH FOR IOMT

In this section, we detail our proposed semantic-based approach as depicted in Figure 1 for patient monitoring through MCOs. This approach is based on four mains phases. The first phase describes the data collection process via the MCO and the patient medical records. In order to understand this data, a semantic modelling representation is suggested by defining their sources and their contexts in relation with either the MCO or patient. As a result, we obtain a HealthIoT ontology that will be analysed by proposing three categories of SWRL rules. The first ones are used to configure and manage the MCO function state. The second ones are highlighted to diagnose the patient state and to predict possible health complication risks. The last category is defined to notify end-users by sending suitable alerts. These three previous phases represent the knowledge-

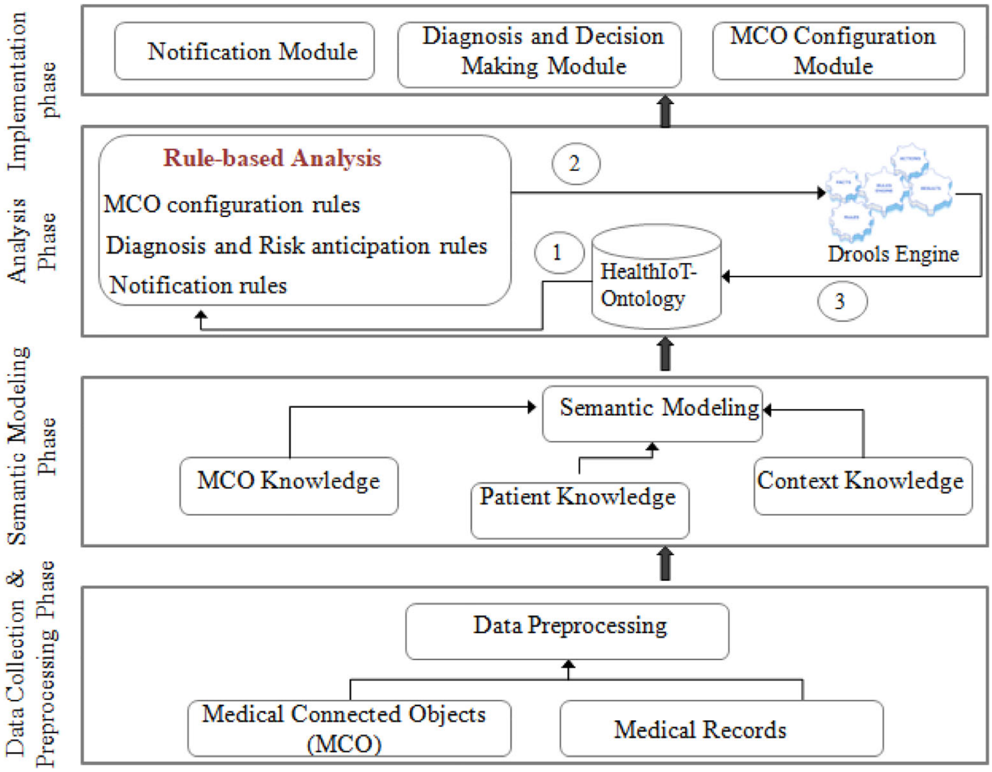


FIGURE 1 Semantic-based context-aware approach

base that will be exploited in our implementation phase to provide the appropriate services for end-users through a friendly user interfaces. These phases will be well detailed in the next sections.

5 | DATA COLLECTION AND PREPROCESSING PHASE

In the case of the IoMT, the patient data to be analysed can be collected from heterogeneous sources. Not only the patient's personal records but also MCOsare exploited to perform reliable disease management and treatment.

5.1 | Data from medical connected objects

In managing and monitoring gestational diabetes, doctors pay attention to patient information that comes from several sources. Blood glucose monitoring devices are exploited for continuous monitoring of blood glucose levels. Therefore, to avoid health complications during pregnancy, diverse other measurements should be taken into account, such as blood pressure, heart rate, cholesterol, patients' activity. In this context, patients consider other medical objects, namely ECG monitoring devices, blood pressure monitoring devices and smartphones containing sensors for activity tracking. Furthermore, according to Abu-Elkheir, Hayajneh, and Ali (2013), data captured through connected objects are classified into two distinct categories: technical data which describes the general context of the data collection process (time, Id sensor, space, MCOs properties, etc.) and data relative to the monitored patient (measurement, unit of measurement, etc.). Figure 2 represents an example of temperature data obtained from medical object in JSON format, where the red colour designates the technical data and the blue colour designates the health data. In this study, we use various data sets (CSV format) from the physiobank,[6] namely temperature, cholesterol, blood pressure, blood glucose, and heart rate. PhysioBank is a large and growing archive of well-characterized digital recordings of physiologic signals and related data for use by the biomedical research community. It is one of the resources of the National Institutes of Health,[7] which is intended to stimulate current research and new investigations in cardiovascular studies and other complex biomedical signals Goldberger et al. (2000). These data sets contain numeric and string data type.

FIGURE 2 Obtained data from sensors


```
{
  "messageID": "urn:uuid:be422ea8-289d-49fa-bd39-6a48f4711c75",
  "messageTime": "2014-08-20T14:32:56.125Z",
  "message": {
    "SensorID": "urn:uuid:8f5308d5-a1ca-4ad4-9a7f-3a70d4177551",
    "SensorName": "Sensor1",
    "Battery-state": "50%",
    "Sensor-Type": "Temperature-Sensor"
    "measureName": {"Temperature"},
    "measureType" : "numeric",
    "measureAcquire" : "sample",
    "measureUnit" : "°C",
    "value" : ["29.3"],
    "valueMax": ["45"],
    "valueMin": ["26"]
    "valueTime" : ["2014-08-20T14:32:56.125Z"]
  }
}
```


5.2 | Data from medical rapport

To provide a precise and suitable treatment for patients, doctors should not only rely on data from mobile objects. In this regard, they need to refer to patients' medical records as another source of healthcare data. This source contains basic patient information (age, sex, name, address), laboratory test data, symptoms, patient medical record, and medical family history. In our work, these valuable information are provided by three domain experts (doctors) from their patients' personal health records (PHR). In that phase, the SNOMED-CT[8] terminology was exploited to represent this clinical information as it contains the largest clinical terminology, in which medical terms and their synonyms, are treatable with machines.

5.3 | Data preprocessing

Due to the ambiguous, heterogeneous and noisy data acquired from the MCOs, a preprocessing phase should be performed to reduce and remove erroneous and unusual data. First, we apply a data cleaning phase that consists in removing data with values outside the IoT devices thresholds. In fact, each device has a maximum and a minimum range. Healthcare data with values outside this range are considered as erroneous data that will be removed. Missing data are also removed. Second, we carry out a normalization phase before integrating this data in the ontology to avoid such inconsistencies. For example we have changed the time format (from 'YYYY/MM/DD hh:ss:mm' to 'YYYY-MM-DDThh:ss:mm') using the ISO 8601 standard adopted by SNOMED-CT.

In order to make this data understandable and interpretable by MCO and IoMT-systems, the next section will be devoted to the formal representation of the MCO and the healthcare domain knowledge and their relationships. The OWL2 (Motik et al., 2009) is used for the formalization of the knowledge domain.

6 | SEMANTIC MODELLING PHASE

In this phase, a HealthIoT ontology (Figure 3) is proposed for the following reasons:

- Defining a unified model of the collected data and linked it with their contexts. This model will be shareable and exploited between objects as well as between humans.
- Facilitating the discovery, integration, manipulation, and configuration of clinical devices.
- Supporting reasoning mechanism on the defined context to infer intelligent decision.

For this end, we aim to extend our proposed HealthIoT ontology (Rhayem, Mhiri, & Gargouri, 2017) in order to cover and express diverse contexts that affect the diagnosis and monitoring of both MO's and patients' states missed in the previous version.

Furthermore, to build the present ontology, we relied to some relevant existing one such as SSN (Compton et al., 2012) through the *ssn* prefix, IoT-O (Seydoux et al., 2016), IoT-lite (Bermudez-Edo et al., 2016), with the *iot-lite* prefix, Time ontology (Hobbs & Pan, 2006) with the *To* prefix, Geonames-ontology through the *geo* prefix and MOO ontology (Wannous, Malki, Bouju, & Vincent, 2013) through the *moo* prefix.

Formally, we define our ontology as 3-tuples: O = (C, A, I) where:

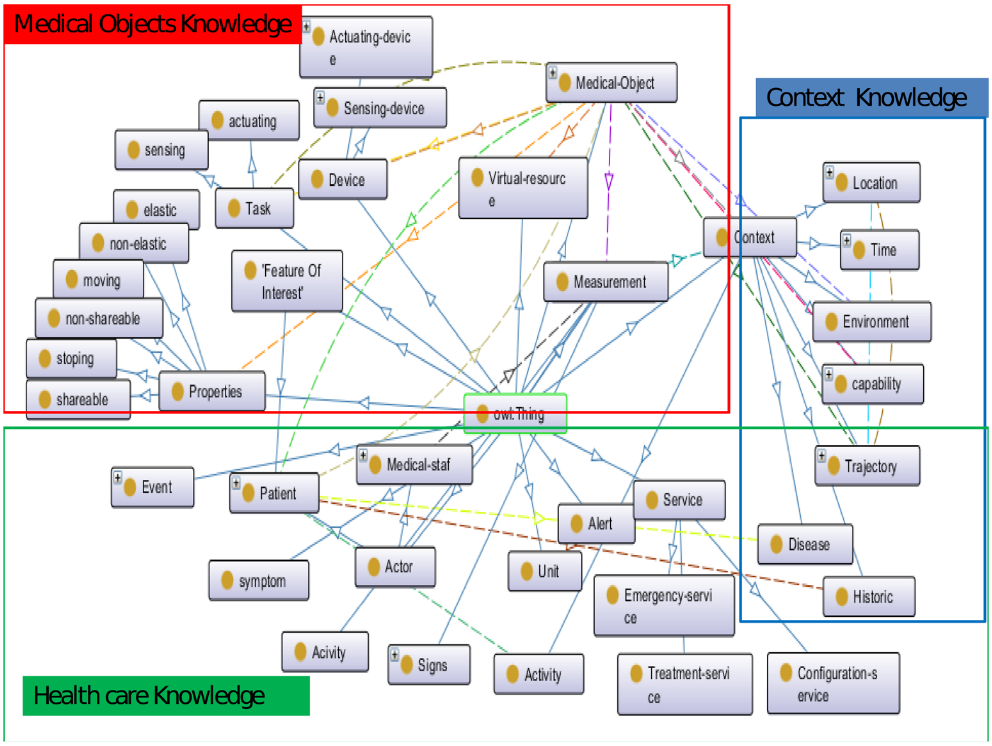


FIGURE 3 HealthIoT ontology

- C: set of concepts
- A: set of axioms between concepts
- I: set of instances of each concept

The main concepts of our ontology are classified into three categories: concepts that represent the knowledge about MCO, the knowledge about the patient states and that about their contexts.

6.1 | MCO knowledge

This step is conceived to model the heterogeneous MCOs and their specificities. The main defined concepts are as follows:

HIoT:Medical-object represents the semantic of heterogeneous MCOs used for remote patient monitoring. For example, the blood glucose monitoring device, blood pressure monitoring device, smartphone, and the medical box represent the MCOs used to monitor pregnant woman who has a gestational diabetes disease.

HIoT:virtual-resource class is proposed to define one of the main IoT goals, which is the virtualization of real-world objects in order to facilitate their management and configuration.

ssn:Device it is a concept extended from the SSN ontology and has two sub-classes: ssn:Sensing-device and iot-lite:actuating-device. The first represents medical-sensor and RFIDs tags which are responsible for the detection of the occurring event and the second describes the actuators acting on the environment. The sensors used for gestational diabetes monitoring such as the blood glucose sensor, the blood pressure sensor, the ECG sensors, and so one, are presented as instances of the sensing device concept. The vibrator, screen, alarm represent the instances of the actuating device concept.

HIoT:properties represents the properties of the used connected-objects. Thereby, we extend some properties from cloud resource that are satisfied by IoT resources such as shareable/non-shareable, elastic/non-elastic, limited and not-limited. Other properties that we can take into consideration in the IoT are 'moving' and 'stop'. These properties are modelled as sub-classes of 'HIoT:IoT-properties' concept. Details about these properties are given in Table 4.

HIoT:Task: it allows the description of the allocated task by the connected objects and the embedded devices (e.g. sensing blood glucose level, triggering treatment alerts).

6.2 | Patient knowledge

In order to represent the health state of the monitored patient, it is necessary to represent some knowledge from the medical sector. At this level, we adopt the Systematized Nomenclature of Medicine Clinical Terms (SNOMED-CT) standard. These concepts can be briefly described as follows:

HIoT:Measurement is designed to represent the semantics of massive quantity of health data obtained from MCOs. It has two sub-classes HIoT:signs and HIoT:Activity. The HIoT:signs defines the detected vital signs of the patient such as the blood glucose, the blood pressure, heart-beat, and so on which are modelled as sub-classes of this concept. HIoT:Alert contains different categories of alerts that can be generated by the actuator device. These alerts can be for objects management or for patient monitoring (treatment adjustment, emergency call for ambulance).

HIoT:Event represents an abnormal detected event from the MCO. It refers to the healthcare event such as hyperglycemia, hypertension, etc.

HIoT:Risk: represents the health complications of uncontrolled disease that may happen.

HIoT:Actor determines the principal actors in the healthcare domain, such as HIoT:Patient, HIoT:medical-staff.

HIoT:Service describes various services that can be generated by the MCOs. These services can be classified into several categories such as treatment services (HIoT:treatment), emergency services when the patient's state is critical (HIoT: emergencyservice) and configuration services which contain the state of the connected objects and the proposed solution.

HIoT:Symptom defines the changes in patient behaviour and sensations about the disease.

6.3 | Context knowledge

HIoT:Context characterizes the MCOs and the obtained data about the monitored patient. In fact, the state of both MCOs and the patient's health changes continuously according to several factors. It is fundamental to consider these factors during the configuration of the MCO state and during the diagnosis of the patient's state in order to propose precise and suitable services.

6.3.1 | Context related to the medical objects deployment

- *To:Time*: describes the MCOs' employment time and the temporal validity of their captured data stream. It has several sub-classes extended from the time ontology as for instance with To:duration, To:instant, To:interval.
- *goe:Location*: describes the surrounding environment of the employed objects. This concept has two subclasses, including the Indoor-Location and Outdoor-Location in order to express the functioning of the connected objects in a large scale.
- *Moo:Trajectory*: extended from MOO ontology (Wannous et al., 2013). It allows representing the mobility characteristics of the connected objects. Trajectory refers to a list of locations that the object crosses during a predefined period. This concept is related to the *Location* concept with 'has-source' and 'has-destination' object properties and to the *Time* concept with 'starts' and 'ends' properties.

TABLE 4 IoT resources properties

Properties	Definition
Shareable	IoT resources can perform two task at the same time
Non-shareable	IoT resources is capable to execute just one task at a given time
Limited	In almost of cases IoT resources have a maximum capacity as for instance with battery lifetime and energy consumption that if it is reached then the IoT resource is no longer working
Non-limited	IoT resources have unlimited capacity
Elastic	It is possible to add/remove resources in order to increase their capability (memory, lifetime, response time, etc.)
Non-elastic	There is no possibility to change the capability of IoT resources
Stop	IoT resources are deployed in a specific environment during a predefined period
Move	IoT resources are in moving state if their environment of deployment change during time

Abbreviation: IoT, Internet of Things.

- *Capability*: is defined by the HIoT:Capability class. It represents the network context, the resource context, and the sensing and actuating capability context (e.g. energy capability, memory capability, life cycle capability). HIoT:Capability has several sub-classes HIoT:Sensing-Capability, san:Actuating-Capability, HIoT: Tags-capability, HIoT:network, and HIoT:MO-Capability concepts.
- *Environment*: is modelled with the HIoT:Environment concept, which determines different factors (humidity, temperature, etc.) that can influence the state of the connected objects and the validity of the detected measurement.

6.3.2 | Context related to the monitored patient

To facilitate the management of complex state and provide the suitable treatment, modelling the context relative to the patient is a promising solution. The main proposed classes in our model are described below.

- *HIoT:Disease*: in the health care domain, it is intrinsic to take into account several contexts like the patient disease. For example, in the general case, a person who has a temperature value greater than 37°C, he has a fever, but for a patient suffering from hypertension disease, he has a fever when the temperature value is greater than 36.5°C.
- *HIoT:Historic*: represents medical information about patients such as their diseases, their causes, symptoms, historic treatments, and so on. This knowledge helps to provide correct diagnosis.
- *HIoT:Patient*: is a primordial context in the healthcare domain. It is a sub-class of 'ssn:FeatureofInterset' concept, which refers to the observed and controlled element. This concept defines personal information such as age, sex, weight, etc. that play a primordial role during the diagnosis phase.
- *HIoT:Activity*: defines the patient's activity (e.g. sleeping, running, walking), which are detected by specific sensors such as cameras, accelerometers during health measurements monitoring.

6.4 | Axioms modelling

A set of axioms, between HealthIoT ontology concepts, which cover the union, the disjoint and the specialization relations are illustrated in Table 5. Therefore, in order to represent how these concepts are related to each other, we define several semantic relationships, some of them are highlighted in Table 6.

As example, the *Patient* class has the relation '*has-object*' with the *Medical-object*. *Medical-object* class is associated with the concept *Device* via the object property '*contains*'. To define the role of the Medical-Object class, which is the surveillance of a *Patient*, we propose the object property '*monitors*' with the range domain ssn:FeatureofInterest and Patient concepts. The objects properties ('*has-location*' and '*has-time*') are associated between the *Medical-object* and both *Location* and *Time* concepts respectively. The object property '*analysis*' is assigned between the *Doctor* concept and the *Measurement* concept.

7 | ANALYSIS PHASE

After the data collection and the semantic knowledge modelling phases, proposing a rule base in order to interpret and exploit this knowledge is a necessary step. Thereby during this phase, we propose and implement a reasoning process as detailed in Figure 4. It is basically composed of two main steps detailed below.

TABLE 5 HealthIoT's axioms

Axiom
Sensing-device $\subseteq$ Device; Actuating-device $\subseteq$ Device
Patient $\subseteq$ Actor; Medica-staff $\subseteq$ Actor; Patient $\subseteq$ ssn: Feature-of-interest
Context $\equiv$ Time $\sqcup$ Location $\sqcup$ Trajectory $\sqcup$ Capability $\sqcup$ Environment $\sqcup$ Disease $\sqcup$ Patient $\sqcup$ Activity $\sqcup$ Historic
Service $\equiv$ Treatment-service $\sqcup$ Emergency-service $\sqcup$ Configuration-service
Contains $\equiv$ embedded-in
Outdoor Location $\subseteq$ Location; Indoor Location $\subseteq$ Location
Instant $\equiv$ Time; Interval $\equiv$ Time

TABLE 6 HealthIoT's objects properties

Object-property	Domain	Range
Contains	Medical-object	Device
Monitors	Medical-object	Feature-of-interest
Has-location	Medical-object	Location
Detect	Medical-object	Measurement
Worn-by	Device	Patient
Has-object	Patient	Medical-object
Has-risk	Patient	Risk
Allocate	Medical-object	Task
Has-activity	Patient	Activity
Analysis	Doctor	Signs
Propose	Doctor	Treatment
Has-treatment	Patient	Treatment
Has-symptom	Patient	Symptom
Starts	Medical object	Instant
Finish-at	Medical object	Instant

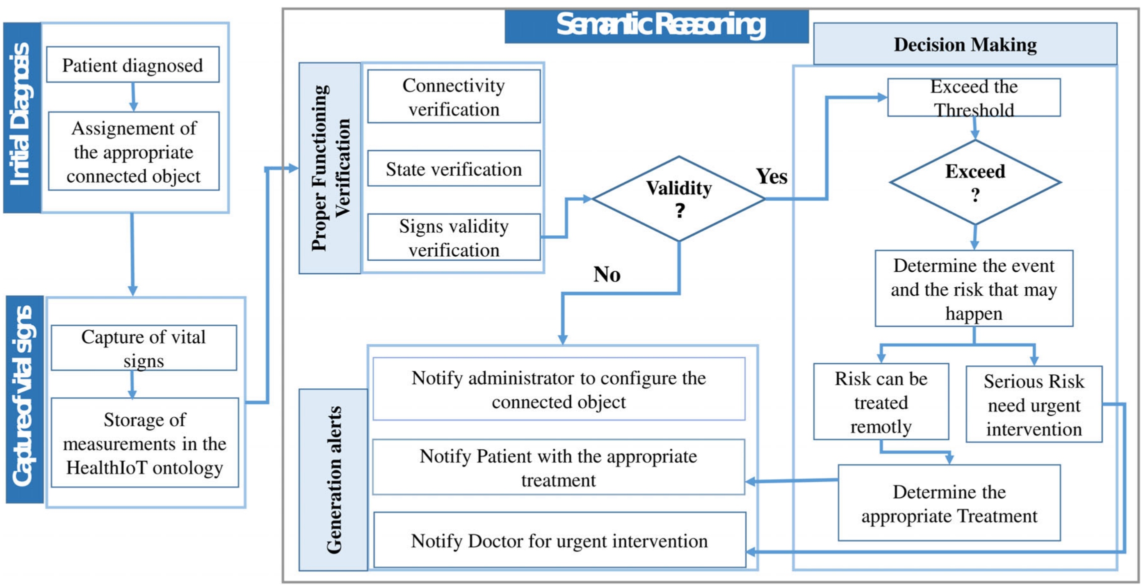


FIGURE 4 Reasoning process

- Initial diagnosis and data collection step: this phase is carried out by the doctor and the MCOs. Firstly, the doctor diagnoses the patient and recommends the suitable object to be used. Then, the detected measurements of this object are stored in the HealthIoT ontology.
- Reasoning step: here, the collected data are analysed. In fact, several rules are developed based on the SWRL language. These rules consists of an antecedent part specifying the condition that must be met and the consequent part defining the fact that may happen. Our rules are formally defined according to the ECA structure (On Event if Conditions do Actions) (Poulovassilis, Papamarkos, & Wood, 2006). The event part determines the contexts for triggering the rules. The condition part represents a set of circumstances that should be achieved. The action part specifies the list of actions to be performed if the conditions will be held. The proposed rules are classified into two categories: rules for connected objects' management and others for diagnosis, treatments and notification proposal. These categories will be detailed with regards to the gestational diabetes context.

7.1 | Medical objects management

To exploit the MCOs in a reliable and effective way, it is necessary to ensure and check their proper functioning, their adaptability level with diverse contexts and their ability to perform configurations.

In this section, we develop diverse rules some of them are described below, which mainly focus on: (a) the diagnosis of the objects state, (b) the allocation/deallocation of tasks, and (c) the verification of their capabilities. We present in \ref{MOM} some SWRL rules for MCOs management in accordance with the proposed use case.

Determine the mode of MCOs: Connected objects can have three different modes:

- Active mode, which verifies that the object is currently active and it is not available to be, used for other tasks.
- Standby mode: verifies that the object finalizes its work and it becomes available for other tasks;
- Passive mode: indicates that the state of the sensor is out of order and it is not available for new tasks that implies to be replaced by another.

These states should be verified using the time context. For example, the standby mode verification consists of:

Event: A MCO contains a sensing device with a blood glucose type and used by a pregnant woman has finished its task and waited for another one (the instant when the sensor accomplishes its task should be before the actual time). This event was triggered thanks to the temporal built-ins ('temporal:before' and the subject 'now') used from the temporal ontology.

Condition: The lifetime of the sensing device should be after the actual time. For that, we use the temporal built-ins 'temporal:after'.

Action: The medical object becomes in standby mode.

rule: "Standby mode verification"
When
Medical-object(?o) ∧ Sensing-device(?s) ∧ contains (?o,?s) ∧ has-type(?s, "blood-glucose-sensor") ∧ has-user(?o,?p) ∧ sexe(?p,"woman") ∧ has-state(?p, pregnant) ∧ finish-at(?s,?f) ∧ has-value(?f,?v) ∧ temporal:before(?f, "now")
IF
has-life-time(?s,?t)∧ has-value(?t,?v) ∧ temporal:after(?t, "now")
Then
has-state(?s, "standby")

Verify the availability of MCOs: In this category, the proposed rules determine if the MCOs are available for new tasks or not. These rules depend on the result of the verification of the mode rules. If the MCO was in active or passive state, it is not available. However, if it is in a standby mode, it becomes available to execute other tasks. The proposed example consists of:

Event: a MCO that contains a sensing device with a blood glucose type is used by a pregnant woman.

Condition: the MCO is in a standby mode.

Action: the MCO is available to execute a new task (e.g. the detection of the blood glucose level after 2 hr).

rule: "Availability verification"
When
Medical-object(?o) ∧ Sensing-device(?s) ∧ contains (?o,?s) ∧ has-type(?s, "blood-glucose-sensor") ∧ has-user(?o,?p) ∧ sexe(?p,"woman") ∧ has-state(?p, pregnant)
IF
has-state(?s, "standby")
Then
availability(?o, true)

Task allocation: The main goal of these rules is to allocate/deallocate tasks for MCOs. They are based on the verification of the mode and the availability rules. Therefore, if the MCOs is available, it can allocate a new task. For example, the suggested rule in this article is formed by:

Event: a MCO contains a sensing device with a blood glucose type turns passive (e.g. lifetime exceeded).

Condition: another MCO contains a sensing device with the same type of the previous MCO is available to execute a new task.

Action: the task of the first MCO is allocated by the second one that will be attached to the monitored patient.

rule: "Task Allocation"
When
Medical-Object(?o1) ∧ Sensing-device(?s1) ∧ contains(?o1,?s1) ∧ has-user(?o1,?p) ∧ sexe(?p,"woman") ∧ has-state(?p, pregnant) ∧ availability(?s1, false) ∧ has-type(?s1,?type1) ∧ task(?t) ∧ allocated(?o1,?t)
IF
Medical-Object(?o2) ∧ Sensing-device(?s2)∧ contains(?o2,?s2) ∧ has-state(?s2, "standby") ∧ has-type(?s2,?type2) ∧ swrlb:stringEqualIgnoreCase(?type1,?type2)
Then
allocated(?o2,?t) ∧ deallocate(?o1,?t) ∧ has-user(?o2,?p)

Capability Verification: To examine the proper functioning and capabilities (battery level, RAM memory, energy consumption, etc) of the medical objects, it is very important to propose various rules. The following rule consists of:

Event: MCO executes a task.

Condition: its battery level is 10%.

Action: the state of the battery is Low and the mode of its sensing-device becomes standby (sleep state) to save energy consumption.

rule: "Battery level verification"
When
Medical-Object(?o) ∧ battery(?b) ∧ Sensing-device(?s)∧ contains (?o,?s) ∧ allocated(?o,?t) ∧ has-battery(?o,?b)
IF
has-value(?b,0.1)
Then
state-battery(?b,"Low") ∧ has-state(?s,"standby")

Mobility Verification: MCOs can be either in fixed or moving states. In fact, moving state defines their dynamic position that changes continuously instead of the fixed one that designates their constant location. Verifying this state needs spatio-temporal data. Therefore, based on the *temporal:duration* built-ins, and the *Time*, *Location* and *Trajectory* contexts, we proposed an SWRL rule that determines if the location of this object changes. We have considered a time interval depending on the estimated period needed for the patient monitoring task that takes into account the patient's state and the complexity of the disease. For example, we supposed that a pregnant woman needs to monitor her blood glucose eight times per day, separated by 2 hr. In these times, we aim to control the mobility of the MCO. Accordingly, it will be easier to allocate tasks in case of failure of MCO by considering only the nearest objects. In addition, it helps to control the activity of the patient. It consists of:

Event: MCO has a trajectory that is composed of a set of crossed locations during an interval of time.

Condition: the location is the same during 2 hr.

Action: MCO object is in stopping state and consequently the patient is motionless.

rule: "Mobility verification"

When

Medical-object(?o) ∧ Sensing-device(?s) ∧ contains (?o,?s) ∧ has-type(?s, "blood-glucose-sensor") ∧ has-user(?o,?p) ∧ sexe(?p,"woman") ∧ has-state(?p, pregnant) ∧ Trajectory(?t)∧ has-trajectory(?o,?t) ∧ has-source(? t,?l1) ∧ has-name(?l1,?m)∧ has-destination(?t,?l2) ∧ has-name(?l2,?n)∧ starts(?t,?i1) ∧ ends(?t,?i2)

IF

swrlb:stringEqualIgnoreCase(?m,?n) ∧ temporal:durationEqualTo (2,? i1,?i2, "Hours")

Then

has-state(?o, "stopping")

7.2 | Patient state diagnosis and decision making

One of the main contributions of this work is to propose a decision-making process namely Measure-Event-Risk-Treatment-Alert (M-E-R-T-A) that takes into account the whole remote diagnosis process for the patient. M-E-R-T-A starts with the analysis of the obtained measures, then the detection of the health event that may happen, the prediction of risk complication, and finishes with the proposition of the adequate treatment and the notification of the patient. Figure 5 shows an example that allows interpreting the detected data with a Glycemia sensor-based on M-E-R-T-A. Thereby, the analysis of glycemia level leads to the detection of hyperglycemia event and the possible risk that may happen as the foetal loss for the pregnant woman. After that, the next phase determines and notifies the patient with the appropriate treatment (Metformin Mylan).

To perform this process, we develop diverse SWRL rules to treat five different health measurements (temperature, blood pressure, heart rate, blood glucose, and cholesterol). In the next sub-sections, we describe some rules in accordance to the proposed use case (gestational diabetes context).

Validity of data: For the purpose to analyse the obtained data in real-time, we define the following to verify the validity of the blood glucose. It consists of:

Event: MCO detects blood glucose level of a pregnant woman.

Condition: the deadline of the obtained blood glucose is greater than the time required for data access and analysis by the doctor. To verify this condition we exploit the temporal SWRL built-ins. *Temporal:before* and the subject "now" that refers to the actual time.

Action: The blood glucose is valid to be processed and analysed.

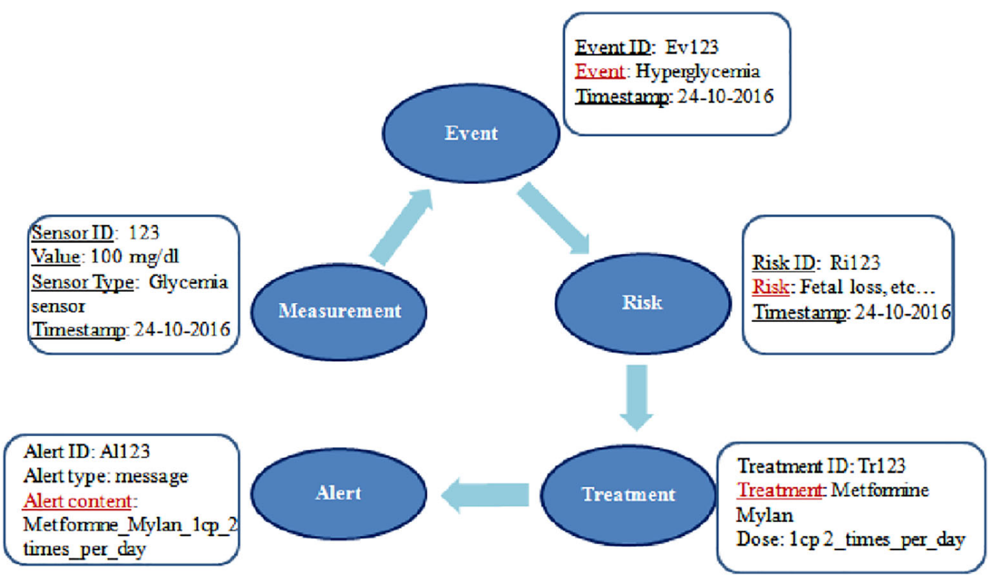


FIGURE 5 M-E-R-T-A: diagnostic and decision-making method

rule: "Validity of the Blood glucose level"
When
Medical-object(?o) ∧ Blood-glucose(?t) ∧ detect(?o,?t) ∧ has-duration(?t,?d) ∧ has-start(?d,?s)∧ has-finish(?d,?e)
IF
temporal:before(?s, "now") ∧ temporal:after(?e, "now")
Then
validity(?t, true)

Events detection: These rules are proposed to enable medical staff to predict and detect events on time. For this end, we define several SWRL rules which aim to examine the patients' vital signs from different contexts in real-time and to provide an adequate solution. For example, the next rule identifies the hyperglycemia event (Gestational diabetes) for a pregnant woman. Therefore, in the normal case, hyperglycemia is diagnosed when the blood glucose level is greater than or equal to 126 mg/dL. But, in the case of pregnant woman, it is diagnosed if it is greater than or equal to 92 mg/dL. This rule consists of:

Event: MCO detects blood glucose level of a pregnant woman.

Condition: The detected blood glucose is valid and it is greater than 92 mg/dL and the pregnancy is meanwhile the forth and ninth months. We use the temporal built-ins "temporal:durationGreaterThan" and "temporal:durationLessThan" to analyse the pregnancy duration of the patient.

Action: Hyperglycemia event is detected.

rule: "Hyperglycemia event detection"
When
Patient(?p)∧ sexe(?p, "woman") ∧ has-state(?p, pregnant) ∧ start-at(pregnant,?s) ∧ temporal:durationGreaterThan (4,?s, "now", "Months")
∧ temporal:durationLessThan (9,?s, "now", "Months")∧ Medical-object(?o)
∧ has-user(?o,?p) ∧ Blood-glucose(?t) ∧ detect(?o,?t)
IF
validity(?t, true) ∧ has-value(?t,?v)∧ swrlb:greaterThan (?v,92)∧ has-unit(?t,?u)∧ has-name (?u, "mg/dl")
Then
has-event(?p, Hyperglycemia) ∧ has-disease(?p, Gestational-diabete)

Risk anticipation: Risk prediction and management are very paramount in the healthcare domain. Thereby, the main goal in this phase is to control and detect potential health risks in order to prevent it and minimize critical crises. For this reason, it is very important to propose a risk management plan that should identify the controlled situation, the critical effect of the result if it happens and its impact.

According to the WHO, uncontrolled diabetes during pregnancy give rise to a very dangerous effect on both mother and child as for instance with the risk of foetal loss, congenital malformations, stillbirth, and obstetric complications. However, the degree of severity of these risks depends on other factors and symptom such as hypertension, cramping, age greater than 40 years and so on. The next rule is formed as:

Event: an hyperglycemia is detected in a pregnant woman.

Condition: the woman has another disease (hypertension), her age is greater than or equal to 40, she has a cramping symptom.

Action: This woman has a high risk of foetal loss.

rule: "Risk of Hyperglycemia in pregnant woman"
When
Patient(?p)∧ sexe(?p, "woman")∧ has-state(?p, pregnant) ∧ has-event(?p, Hyperglycemia)
IF
has-event(?p, hypertension) ∧ has-symptom(?p, cramping) ∧ hasage(?p,?a) ∧ swrlb:greaterThanOrEqual(?a, 40)
Then
has-risk(?p, fetal-loss) ∧ has-degree(fetal-loss, "High")

Treatment proposition: In this phase, diverse rules are defined to assist doctors in making an efficient and suitable treatment according to the diagnosis results. The proposed treatment can be a lifestyle recommendation, drugs proposition, and adjustment, or emergency service that requires the quick intervention of the medical staff. The next rule describes an emergency service for a pregnant woman. This rule is defined as:

Event: an hyperglycemia is detected in a pregnant woman.

Condition: the woman has a high risk of foetal loss.

Action: the woman needs an emergency service e.g. ambulance).

rule: "Emergency service proposition for pregnant woman"
When
Patient(?p) ∧ has-risk(?p, fetal-loss)
IF
has-degree(fetal-loss, "High")
Then
need(?p, ambulance)

Rules for alert generation: A generated alert from the MCOs is classified into three categories according to their importance (normal, medium and urgent). The normal alert is automatically produced by the MCOs where the analysis of the data is performed by the controller devices, and the decision is provided within the actuator devices. This kind of alert is usually used in simple cases (e.g. message contains the value of the detected signs). The medium alert is proposed in cases that need the intervention of medical staff, the data would be transferred to the healthcare professionals to analyse it and to propose the adequate alert that would then be sent to the MCOs of the patient. The urgent alert is provided when the medical staff detects a critical case, which needs urgent intervention. The following rule represents an example of a normal alert, which consists of:

Event: hyperglycemia is detected in a pregnant woman.

Condition: The woman has a MCO that contains an alarm actuator.

Action: The alarm state will be "ON" and the received message was "High blood glucose, contact your doctor".

rule: "Normal Alert"
When
Patient(?p) ∧ has-event(?p, Hyperglycemia)
IF
Medical-Object(?o)∧ contains(?o, Alarm) ∧ has-user(?o,?p)∧ sexe(?p,"woman") ∧ has-state(?p,"pregnant")
Then
has-state(Alarm, "ON") ∧ has-message(Alarm,"High blood glucose, contact your doctor")

The next one describes an emergency alert triggered in critical cases. It is formed as:

Event: the patient (pregnant woman) needs emergency service (ambulance).

Condition: a hospital has an available ambulance.

Action: The actuator of the ambulance is on state "ON" and has a message, which indicates the name and the location of the corresponding patient.

rule: "Emergency Alert"
When
Medical-Object(?o) ∧ has-type (?o, "ambulance") ∧ actuator(?c) ∧ contains(?o,?c) ∧ Hospital(?h) ∧ has-object (?h,?o)
∧ availability(?o,true) ∧ Patient(?p) ∧ has-name(?p,?name) ∧ located-in(?p,?l)
IF
need(?p,ambulance)
Then
swrlb:stringConcat(?m,?name,?l) ∧ has-state(?c, "ON") ∧ has-message(?c,?m)

8 | IMPLEMENTATION PHASE

Once our knowledge-base is defined referring to previous phases, it is necessary to be exploited by end-users. From this regard, the main goal of this implementation phase is to develop an IoT-based clinical decision support system (IoT Medicare system). This system is integrated with query and inference engine (Drools engine) developed with SWRLAPI, OWLAPI, and Jena APIs which are used to deal with SWRL rules, and SPARQL queries. To provide a suitable decision, this system takes into account the health data that describes the patient's information and technical data that represents the state of the medical objects. The IoT Medicare system consists mainly of three modules: Medical Objects Management, Diagnosis and treatment module, and a Notification module. The connected object management module deals with ensuring the proper functioning of the connected objects. The second module focuses on the analysis and the interpretation of the detected patient vital signs, to treat and prevent diseases. The notification module allows notifying patients with the decision of the doctor.

The reliable exploitation of the IoT system requires a secure actor authentication to protect the accessed information through a password stored in the HealthIoT ontology. After that, the end user is able to ask simply a query using easy ways (button choose, or menu choose). This query is transferred to the knowledge base to run an inference engine (Drools engine). The latter, firstly, loads the ontology on the basis of OWLAPI and executes the developed SWRL rules. Subsequently, it gives the actors the appropriate decision through the obtained inferred results.

Figure 6 presents the general architecture of the developed IoT Medicare system.

8.1 | MCO management module

With the continuous growth of MCOs, a manual monitoring of their states has become infeasible and very hard. Therefore, it is paramount to propose a monitoring system that enables the administrator user to:

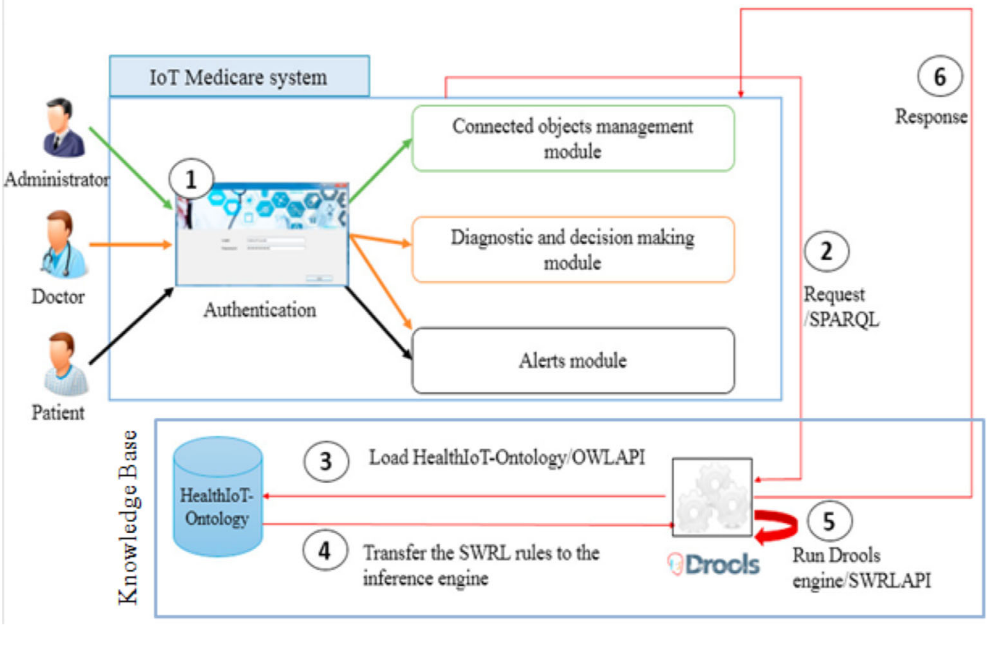
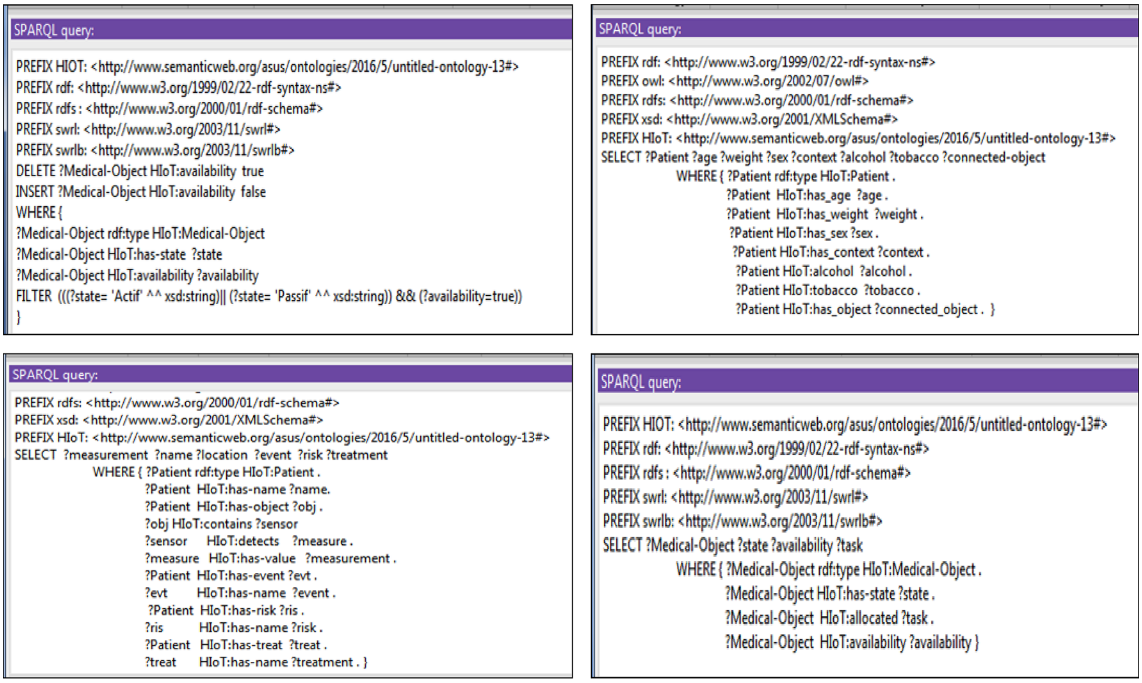


FIGURE 6 General architecture of IoT medicare system



```
SPARQL query:
PREFIX HIOT: <http://www.semanticweb.org/asus/ontologies/2016/5/untitled-ontology-13#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs : <http://www.w3.org/2000/01/rdf-schema#>
PREFIX swrl: <http://www.w3.org/2003/11/swrl#>
PREFIX swrlb: <http://www.w3.org/2003/11/swrlb#>
DELETE ?Medical-Object HIoT:availability true
INSERT ?Medical-Object HIoT:availability false
WHERE {
?Medical-Object rdf:type HIoT:Medical-Object
?Medical-Object HIoT:has-state ?state
?Medical-Object HIoT:availability ?availability
FILTER (((?state= 'Actif' ^^ xsd:string)|| (?state= 'Passif' ^^ xsd:string)) && (?availability=true))
}
```

```
SPARQL query:
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX HIoT: <http://www.semanticweb.org/asus/ontologies/2016/5/untitled-ontology-13#>
SELECT ?Patient ?age ?weight ?sex ?context ?alcohol ?tobacco ?connected-object
        WHERE { ?Patient rdf:type HIoT:Patient .
                ?Patient HIoT:has_age ?age .
                ?Patient HIoT:has_weight ?weight .
                ?Patient HIoT:has_sex ?sex .
                ?Patient HIoT:has_context ?context .
                ?Patient HIoT:alcohol ?alcohol .
                ?Patient HIoT:tobacco ?tobacco .
                ?Patient HIoT:has_object ?connected_object . }
```

```
SPARQL query:
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX HIoT: <http://www.semanticweb.org/asus/ontologies/2016/5/untitled-ontology-13#>
SELECT ?measurement ?name ?location ?event ?risk ?treatment
        WHERE { ?Patient rdf:type HIoT:Patient .
                ?Patient HIoT:has-name ?name.
                ?Patient HIoT:has-object ?obj .
                ?obj HIoT:contains ?sensor
                ?sensor HIoT:detects ?measure .
                ?measure HIoT:has-value ?measurement .
                ?Patient HIoT:has-event ?evt .
                ?evt HIoT:has-name ?event .
                ?Patient HIoT:has-risk ?ris .
                ?ris HIoT:has-name ?risk .
                ?Patient HIoT:has-treat ?treat .
                ?treat HIoT:has-name ?treatment . }
```

```
SPARQL query:
PREFIX HIOT: <http://www.semanticweb.org/asus/ontologies/2016/5/untitled-ontology-13#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX rdfs : <http://www.w3.org/2000/01/rdf-schema#>
PREFIX swrl: <http://www.w3.org/2003/11/swrl#>
PREFIX swrlb: <http://www.w3.org/2003/11/swrlb#>
SELECT ?Medical-Object ?state ?availability ?task
        WHERE { ?Medical-Object rdf:type HIoT:Medical-Object .
                ?Medical-Object HIoT:has-state ?state .
                ?Medical-Object HIoT:allocated ?task .
                ?Medical-Object HIoT:availability ?availability }
```

FIGURE 7 SPARQL queries

- Facilitate the search, the update and the exploitation of these devices.
- Ensure a periodic monitoring of MCOs.
- Help to anticipate problems and provide preventive and predictive maintenance.

The administrator is the responsible for this task. Thus, he is able to monitor the state of the medical object and configure it, add new objects, consult the list of objects, update its properties, among others.

For example, from a given list of objects, the administrator selects the concerned one to be configured. This list is the result of the SPARQL query illustrated in Figure 7d. The latter returns the objects that need a configuration (e.g. object with active mode and with availability true). The administrator can easily change the value of the availability state to false through a user-friendly interface.

The confirmation of this task is insured via the 'UpDate' button, which executes a SPARQL update query (Figure 7a). This query consists of two main operations. The Delete operation removes the 'true' value of the data property availability and the insert operation inserts the 'false' value.

8.2 | Patient state diagnosis module

This module has been designed to describe how healthcare professionals can remotely provide diverse systematic care services including the analysis and diagnosis of the patients' states.

The meaningful interpretation of vital signs obtained from several connected objects; this implies to provide adequate treatments for patients, which presents the main goal of this module. In fact, through a simple authentication, the doctor can perform various functionalities. Firstly, he should specify the appropriate object to be used to monitor the patient's state. Once this object is activated and based on its detected vital signs, he is able to diagnose the patient's state. Then, he can consult the list of patients in charge in order to know their status, their disease record, and followed treatments, notify them with a suitable cure, and so on. When the doctor selects the patient to be monitored, a decision-making interface is displayed in Figure 8. This interface illustrates the obtained vital signs from the patients' medical objects. Accordingly, by clicking on the button 'Diagnostic', the doctor can check the patient's actual state, the possible risk and the appropriate treatment for this predicted event. In this interface, the diagnostic, the risk and the treatment areas are alterable in order to offer the doctor the possibility of updating them because the role of a doctor is irreplaceable. After that, through the button 'Notify Patient' the doctor sends his decision to the patient.

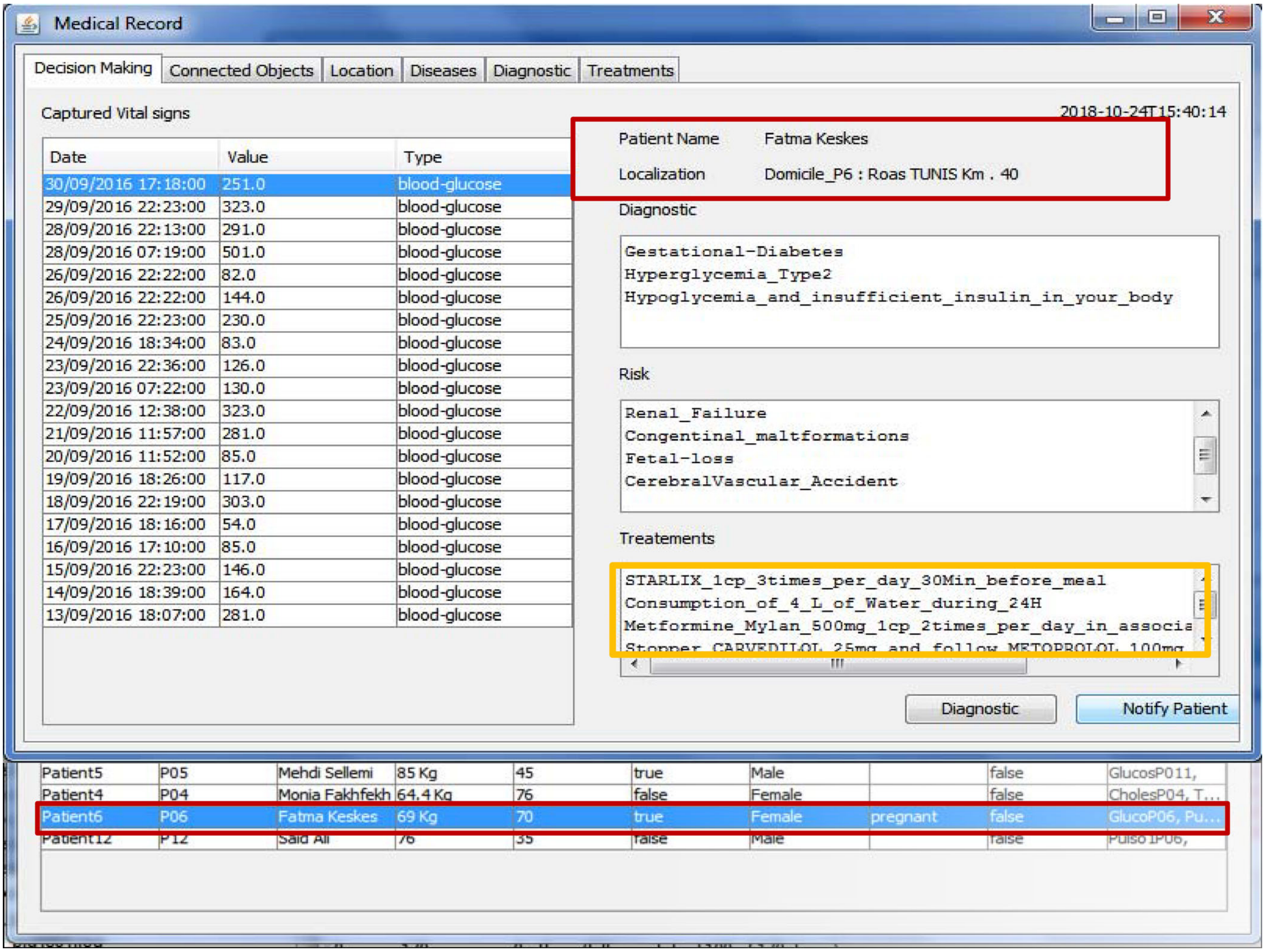


FIGURE 8 Decision-making

8.3 | Notification module

The main reason to design this layer is to make patients capable to receive recommendations and treatments from their doctors and contact them when they face adverse effects following a proposed medication.

This module is very important because it ensures a high health care service delivery during a reasonable time.

Figure 9 represents an example of a notification that contains adequate treatment after the analysis of the state of the selected patient (coloured in red) in the last module and how this notification is saved in the knowledge base 'HealthIoT-Ontology'. This module is composed of a diverse menu. The *profile* menu provides general information about the patient and the suggested treatments by the doctor. The *diagnostic* menu shows the diagnosis events and possible healthcare risks. The *measurements* menu shows the vital sign's value and the detection time. The *treatments* menu contains previous treatment taken by the patient. The *physicians* menu contains general information of the patient's doctor and his web site.

9 | EVALUATION

We evaluate our approach on the functional and technical level. In the technical level, we focus on evaluating the semantic quality of the proposed model (HealthIoT-O). In the functional level, we focus on the reasoning performance and the response time of our developed system 'IoT Medicare system'.

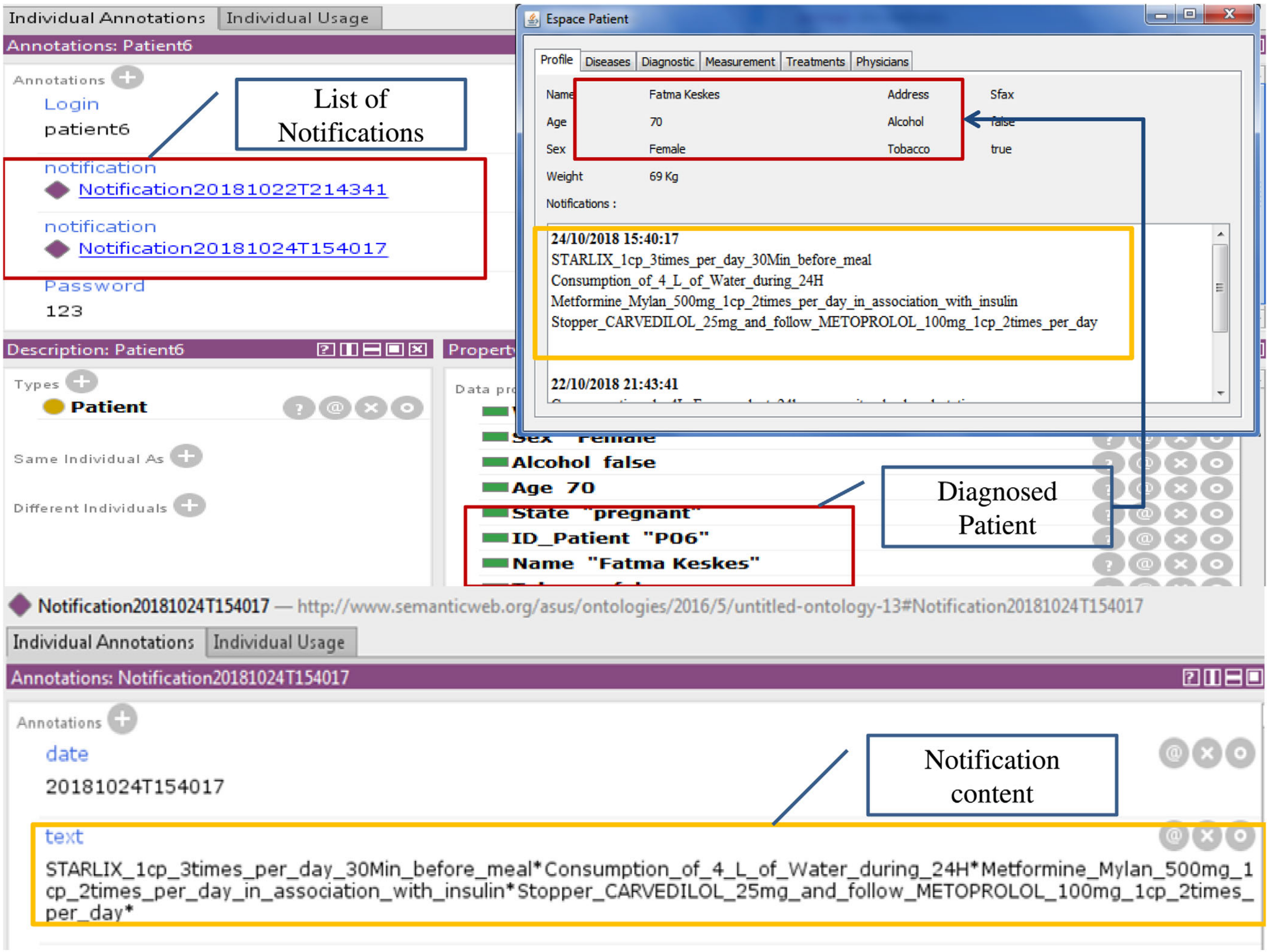


FIGURE 9 Saved notification in HealthIoT-O

9.1 | Technical evaluation: OQuaRE framework

In order to evaluate the quality of our ontology, we applied the OQuaRE evaluation framework (Duque-Ramos et al., 2013), which is mainly based on the Software product quality standards ISO/IEC 25012:2008 (SQuaRE) ISO/IEC (2008). In this work, the authors used the SQuaRE characteristics namely structural, functional adequacy, adaptability, maintainability, operability, reliability, and transferability. Each characteristic was assessed with various sub-characteristics and metrics.

Table 7 recapitulates these characteristics, their definitions, their sub-characteristics, and the related metrics.

For more details about the relative metrics of each sub-characteristic, how each metric is calculated and how the score is assigned, readers may refer to these works (Duque-Ramos et al., 2013, 2014; Duque-Ramos, Fernández-Breis, Stevens, & Aussenac-Gilles, 2011).

Based on these works, our experimentation process is summarized as follows:

1. Firstly, we calculated the value of each metric for each sub-characteristic (note that one metric can be used for several sub-characteristics).
2. Secondly, we assigned a score for each metric that shows the acceptability degree of each measurement. The score range varies between 1 and 5. Where 1 means highly unacceptable, 2 unacceptable and improvement is required, 3 minimally acceptable, 4 acceptable, and 5 exceeds the requirements. The mapping process is well detailed in Duque-Ramos et al. (2011).
3. Then, we calculated the average score of these sub-characteristics that is equal to the mean score of all their associated metrics.
4. Finally, we calculated the average score of each characteristic which is equal to the Mean Score of their sub-characteristics.

Figure 10 depicts the score of each quality characteristics of the HealthIoT ontology. The structural, functional, reliability as well as the operability characteristics are above average, which reflects the good quality of the HealthIoT ontology. However, for the Maintainability and

TABLE 7 OQuaRE characteristics and metrics (Duque-Ramos et al., 2014)

Characteristics	Definitions	Sub-characteristics	Metrics
Structural	Allows evaluating the ontology based on diverse formal and semantic ontological properties	Formal, cohesion, redundancy Tangledness	RROnto, LCOMOnto, TMOnto, ANOnto
Functional adequacy	Evaluates the degree of the ontology to execute concrete function purposes	Controlled vocabulary, consistent search and query, knowledge acquisition, results representation, knowledge reuse	ANOnto, RROnto, AROnto, INROnto, INROnto, NOMOnto
Reliability	Determines the degree of the ontology to maintain the performance level under several conditions	Availability, recoverability	WMCOnto, DITOnto, NOMOnto, LCOMOnto
Maintenability	Determines the flexibility of the developed model to adapt to changes in the environment, requirements, and functional specification	Modularity, reusability, analysability, changeability, modification stability, testability	WMCOnto, DITOnto, NOCOnto, RFCOnto, NOMOnto, LCOMOnto, CBOOnto
Compatibility	Checks how much the ontology can be deployed for different applications and with different software	Replaceability, adaptability	WMCOnto, DITOnto, RFCOnto, NOMOnto, CBOOnto
Operability	Verifies how much the ontology enables users to learn its application	Learnability	WMCOnto, LCOMOnto, NOMOnto, CBOOnto, NOCOnto

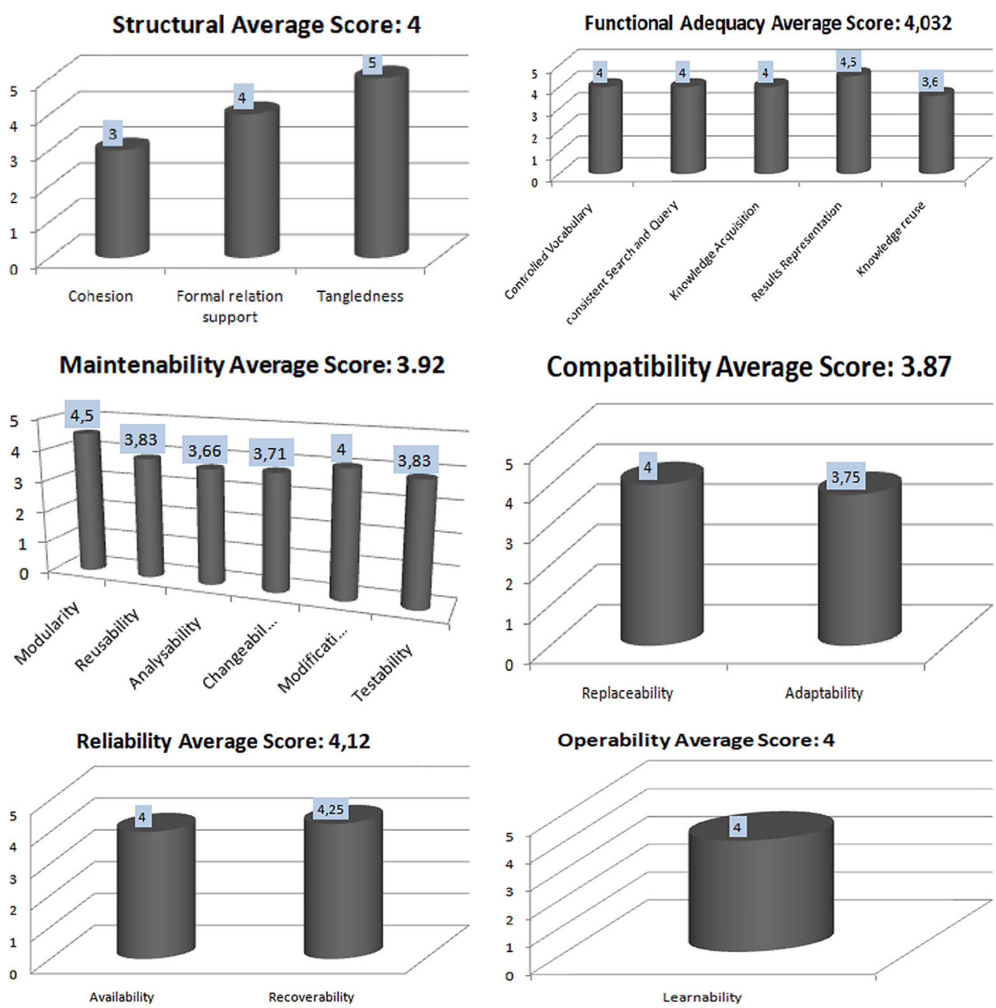


FIGURE 10 HealthIoT-ontology evaluations using OQuaRE metrics

compatibility characteristics, the average score is above 3 (minimally acceptable) but still less than 4. For these characteristics, some metrics should be improved to reach this score. For example, in the maintainability characteristics, LCOMOnto and DITOnto metrics have the score 3, which is minimally acceptable. Consequently, the HealthIoT ontology needs some improvements related to these indicators.

9.2 | Functional evaluation

In this step, we evaluated the reasoning performance of HealthIoT ontology and the effect of the quantity of data obtained from medical devices and their contexts on the response time of the IoT Medicare system.

9.2.1 | Reasoning performance of HealthIoT

To evaluate the effectiveness of our model reasoning, three evaluation measures including Recall, Precision, F-Measure were considered as shown in the following equations. We relied on the contingency table as described in Table 8. We denoted TP, FP, TN, and FN as True Positive (correctly diagnosed instances as required), False Positive (incorrectly diagnosed instances as required), False Negative (incorrectly diagnosed instances as not required), and the True Negative (correctly diagnosed instances as not required).

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{2}$$

$$\text{F-measure} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The values of these measures reflect the relevance level of the inferred axioms by identifying the proper and the ambiguous ones. The precision P is characterized as the capacity of the IoT Medicare system to return the proper inferred axioms to the users. It refers to the portion of the proper inferred axioms among the whole inferred ones. The Recall R measure is characterized by the ability of the system to return few incorrectly inferred results as possible. It alludes to the portion of the correctly inferred axioms by the system among the real identified ones. The F-measure is used to evaluate prediction accuracy by computing both precision and recall.

In our experiment, five different datasets (temperature, blood pressure, blood glucose, cholesterol, and heart rate) were selected from the physiobank[9] database. Ten patients took part in this study. Therefore, in each dataset, we relied on 1,200 data recorded over a period of 1 month in order to monitor these patients (4 measurements perday × 30 days × 10 patients). Consequently, a total of 6,000 data records (1,200 × 5) were stored in the HealthIoT ontology. These datasets contain other additional information, such as the time and the location of these measures. Hence, 18,300 instances (measures, time, locations, symptoms, diseases, drugs, food) were created to form the knowledge base of our clinical decision support system (IoT-Medicare).

In fact, we have implemented diverse rules validated by healthcare experts (three doctors) who helped us calculate the reasoning performance of our knowledge base. First, we proposed 20 rules by taking into account a few contexts (age and sex). These rules assist doctors in their primary diagnosis of a particular disease. Second, we deeply focused on diverse contexts for advanced diagnostic processes (about 35 rules). Tables 8 and 9 show the results of the correctly diagnosed patients by our system compared to those diagnosed manually (by domain experts), in the first and the second cases, respectively.

TABLE 8 Comparing system classification with domain experts classification, in the primary diagnosis

	Correctly diagnosed cases by expert domain	Incorrectly diagnosed cases by expert domain
Correctly diagnosed cases by IoT Medicare system	(2700) TP	(1310) FP
Incorrectly diagnosed cases by IoT Medicare system	(1030) FN	(1020) TN

Abbreviation: IoT, Internet of Things.

TABLE 9 Comparing system classification with domain experts classification with diverse contexts

	Correctly diagnosed cases by expert domain	Incorrectly diagnosed cases by expert domain
Correctly diagnosed cases by IoT Medicare system	(3230) TP	(630) FP
Incorrectly diagnosed cases by IoT Medicare system	(780) FN	(1360) TN

Abbreviation: IoT, Internet of Things.

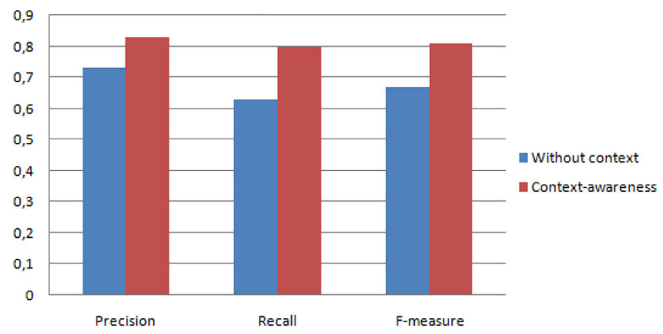


FIGURE 11 IoT-medicare system performance

We recognized that taking into account context-aware reasoning gives a more precise and correct diagnosis and reduce adverse event that usually occur in misdiagnosis cases. Our system reached a precision rate of 83%, a recall rate of 80% and an f-measure rate of 81%.

Thereby, the performance of the developed system was improved as demonstrated in Figure 11.

9.2.2 | Response time of IoT medicare system

This section was devoted to evaluate the effect of data quantity and its contexts on the response time of the IoT Medicare System. Thereby, the response time is defined as:

$$T_{rep} = T_{load} + T_{inf} + T_{query} \tag{4}$$

where T_{load} is the time needed to load the HealthIoT ontology in the Drools engine, T_{inf} is the execution time of the SWRL rules and T_{query} determines the processing time of SPARQL queries to display results to the users.

HealthIoT ontology is made up of more than 80 concepts, 100 object properties, and more than 90 data properties.

In our experiment, we started by using 35 rules. The latter will be increased to 65 rules in the next step. Then, in each experimental phase, we vary the number of instances in the HealthIoT ontology (600, 1,000, 5,000, 10,000, and 18,300). They are related to the measurements (temperature, blood glucose, blood pressure, heart rate, and cholesterol) obtained from a number of patients over a required period.

The simulation is conducted based on the following software platforms: Protege 5.0.1, JVM 1.8.1, Windows 7. The hardware platforms are Intel Core 5GHZ CPU and 4GB RAM.

As shown in Figure 12, when the amount of data stored increases from 5,000 to 18,300, the response time of the processing rules rises from 7.5 s to 14.87 s based on only 35 rules. However, when the number of rules increases to 65, the response time increases from 11.12 to 23.43 s. Thus, the amount of the stored data and the number of the proposed rules that involved complicated context reasoning, can have a significant impact on the performance of the response time.

9.3 | Comparison with the existing approaches

In this section, we conducted a comparative study between the above-mentioned works in Section 3.2.2 and our work. This comparison is based on four main criteria as presented in Table 10. These criteria respond to the goals of our approach.

The coverage criterion aims to determine the coverage rate of IoT concepts in our model compared to other models. It is determined by comparing the HealthIoT concepts with standards in the IoT domain. From this context, we have considered some referenced IoT models, namely IoT-A (Bauer et al., 2013) composed of 16 concepts, IoT-lite (Bermudez-Edo et al., 2016) consisted of 18 concepts, IOT-O (Seydoux et al., 2016)

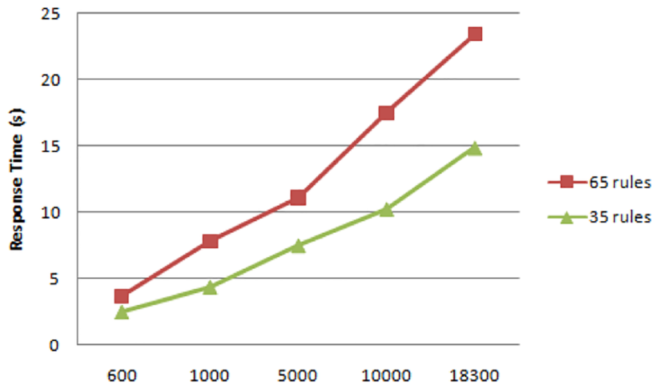


FIGURE 12 Response time of IoT medicare system

that is comprised 28 concepts, and FIESTA ontology composed of 26 concepts (Agarwal et al., 2016). We calculated the coverage value using the following equation:

$$C = RC/TC \tag{5}$$

where C is the coverage rate, RC is the used concepts from the IoT model, and TC is the whole number of concepts of the IoT model. For example, the coverage rate of the healthIoT ontology within the IoT-A model equals to 75%. This rate is obtained by dividing the number of the defined concepts in the HealthIoT ontology that are defined in the IoT-A model (12 concepts) by the number of concepts of the IoT-A model (16 concepts).

The second criterion deals with reasoning tasks. With this criterion, we check the primary objective of the proposed rules; whether it is for device management (DM), disease diagnosis (DiD), disease treatment (DiT), risk prediction (RD), or alert suggestion (Alert). The context-aware criterion identifies contexts treated in each work. The last criterion focuses on the adopted method to evaluate the suggested models.

Based on the comparative table our system differs from other approaches according to several aspects:

- It is based on a generic knowledge base (HealthIoT-ontology) that describes the amalgamation between the basic IoT domain concepts and healthcare concepts. So that, it is useful for other applications in various contexts. It is better than other systems which are based only on a sensor device. Our ontology includes other concepts (actuator, RFIDS tags, Medical-Object). It presents a good coverage value that promotes its applicability. Health IoT covers 75% of the IoT-A model, 25% of the IoT-O, 38% of the IoT lite, and 26% of the FIESTA ontology.
- Unlike other systems, our system ensures configuration and management services for deployed objects to guarantee continuous and reliable patient monitoring.
- It suggests a whole diagnostic process that begins with data collection, diagnosis, risk prediction, treatment suggestion, and triggered alerts. Most of these systems are put forward to accomplish a specific task, such as treatment or diagnosis tasks. None of them has defined the diagnostic process, compared to Chen, Jin, et al. (2016) who focused on a specific application (Hypertension disease).
- It is a context-aware system that treats diverse contexts by taking into account patients' states and medical devices.
- It offers user-friendly interfaces that can be employed by three different users (patients, doctors, and administrators). However, the majority of other systems have been proposed for just one user; patients.
- Our system is flexible as it presents a graphical interface to doctors to help them add or delete new patients and medical objects in the knowledge base.
- It provides patients with other various functions, such as the possibility to contact their doctors via a graphical interface which contains their healthcare information.

10 | CONCLUSION AND OUTLOOK

This article proposed a semantic-based context-aware architectural approach for patient monitoring with MCOs. It was designed based on four fundamental phases that are the data collection and preprocessing phase, the semantic modelling phase, the analysis phase, and the implementation phase. The data collection and preprocessing phase considered two sources of data: data collected from MCOs and data collected from medical records. The semantic modelling phase addressed the representation of knowledge about the MCOs, the monitored patient, and their contexts. The resulted semantic model called 'HealthIoT Ontology' was exploited by defining diverse rules based on the SWRL language in the analysis phase. These rules were suggested for two main objectives: the configuration and the management of the employed objects and the

TABLE 10 Comparison with existing works

Reference	Coverage of IoT concepts	Context-aware	Reasoning	Evaluation								
	IoT-A (16) Bauer et al. (2013)	IoT-O (28) Seydoux et al. (2016)	IoT-lite (18) Bermudez-Edo et al. (2016)	FIESTA-O (26) Agarwal et al. (2016)		DM	DiD	DiT	RP	Alert	Functional evaluation	Technical evaluation
Chen, Jin, et al. (2016)	4/16 = 25%	3/28 = 10%	3/18 = 16%	3/26 = 11%	Patient	No	Yes	Yes	Yes	Yes	Response time	No
Alirezaie et al. (2017)	2/16 = 12%	2/28 = 7%	2/18 = 11%	2/26 = 7%	Time, location, Patient's activity	No	Yes	No	No	No	No	No
Moreira et al. (2018)	1/16 = 6.2%	1/28 = 3%	1/18 = 5.5%	1/26 = 3%	No	No	No	No	No	No	Competency questions	No
Esposito et al. (2018)	1/16 = 6.2%	1/28 = 3%	1/18 = 5.5%	1/26 = 3%	Patient's activity	No	Yes	No	Yes	Yes	No	No
El-Sappagh et al. (2019)	4/16 = 25%	8/28 = 28%	7/18 = 38%	7/26 = 26%	Patient	No	No	Yes	No	No	Competency questions	No
Rubí and Gondim (2020)	1/16 = 6.2%	1/28 = 3%	1/18 = 5.5%	1/26 = 3%	No	No	Yes	No	No	Yes	No	No
Gray our approach	12/16 = 75%	7/28 = 25%	7/18 = 38%	7/26 = 26%	Patient, disease, historic, time, location, trajectory, MCO's capability	Yes	Yes	Yes	Yes	Yes	F-measure, precision, rappel, response time	OQUARE framework

Abbreviations: IoT, Internet of Things; MCO, medical connected object.

patient state diagnosis and decision-making taking into account the alterable context. The implementation phase was focused on the development of an IoT Medicare system for patient monitoring, which integrated both the proposed knowledge base (HealthIoT-O) and the rule base in order to provide diverse services for end-users (doctor, patient, and administrator) according to its deployment context. The evaluation of our approach focused on two objectives: a technical evaluation that interested in the semantic quality of HealthIoT ontology and a functional evaluation that focused on the reasoning performance and the response time of the IoT Medicare system.

The current work offers many challenges and different perspectives which will be addressed in our future research. First, we will focus on the automated extraction of patients' clinical information from electronic sources (electronic health records) by applying natural language processing techniques (NLP) and deep learning approaches. Second, our ontology will be integrated in healthcare standards. For instance, the well-known standard of HL7 Fast Healthcare Interoperability Resources (FHIR) supports health data representation and data exchange between heterogeneous medical systems.

Therefore, we will focus on the alignment of our ontology with other domain ontology in order to enhance its capacity to accommodate different application domains. Moreover, we aim to evaluate the capacity of our approach in the monitoring of patients suffering from viral infections (COVID-19).

In addition, we aim to propose and to implement an intelligent solution to optimize the use of the ontology instances to be then smartly processed and analysed. This solution will be able to define a direct and seamless interpretation of the knowledge base and the system without using the inference engine. By this way, we ensure that the more accurate knowledge we use, the more understandable and reasonable system we can define. In addition, we will focus on the scalability challenge of the IoT-Medicare system in order to be capable to manage the possible huge quantity of data accurately. In this context, Big data technology can be exploited as a solution.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

ENDNOTES

[1] https://www.huffingtonpost.com/josh-stein/the-emergence-of-the-inte_b_6801714.html

[2] https://www-03.ibm.com/press/us/en/pressrelease/49475.wss

[3] https://www.irit.fr/recherches/MELODI/ontologies/IoT-O/

[4] https://www.fiware.org/

[5] http://fiesta-iot.eu/

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[8] http://www.snomed.org/

[9] https://physionet.org/physiobank/

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