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RESEARCH ARTICLE

An IoT-Enabled Ontology-Based Intelligent Healthcare Framework for Remote Patient Monitoring

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ABSTRACT The advancement in automation and medical care technologies in recent decade has changed the traditional medical treatment of patients. Although, these technologies have increased the treatment's precision but the growing number and the complexity of IoT healthcare devices are impacting accuracy along with several other challenges. Moreover, the use of different programming languages, operating platforms and data management methodologies are creating restrictions in safe exchange, integration and reuse of information across different applications. However, with the advent of the semantic web, the semantic technologies are growing in healthcare systems due to the capability of machine interpretation and processing by overcoming the restriction of languages and data heterogeneity. The most common shortcoming in the existing systems are the context-awareness and quality of services and the absence of rich patient ontology; leading towards low accuracy of results. To this aim, this paper provides a smart health framework, consisting on the collection and processing of IoT data (related to patient conditions and context). The framework is supported by the patient ontology along with SWRL rules for better decision making that consider different features (context-awareness and quality of services) differently that results in the improved accuracy. In the evaluation process the proposed work has achieved an accuracy of 89.81%. This work will help the practitioners to treat the patients in a better way.

INDEX TERMS Healthcare framework, patient monitoring, IoT healthcare devices, patient ontology, medical decision support system.

I. INTRODUCTION

Mergency services are important because these save lives through rapid assessment, timely interventions, and transportation to the nearest healthcare center. These technology-based emergency services have been emerged from networks, artificial intelligence, knowledge engineering and system engineering. These technological services have created different opportunities to build advanced applications in order to provide highly dynamic, diverse, and efficient healthcare services to the patients by providing decision-making support to healthcare service providers [1].; For example, in the context of an elderly patient, the wearable devices can monitor and detect the health problem and can send an alert to emergency service providers who can provides timely and appropriate treatment to the patients. It also helps them to monitor their states.

According to the forecast of the World Healthcare Organization (WHO), by 2030, old age (above 60 years of age) population will reach to 1.4 billion of the total population

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of the world [2]. Another study indicates that chronic diseases cause approximately 60% of deaths worldwide by contributing approximately 46% burden on the global financial system due to chronic diseases [3]. However, Center for Disease Control and Prevention claims that the people of America suffering from chronic diseases at 65 or more years of age can expect to live longer by another 19.3 years by carefully managing chronic conditions by staying healthy. Whereas, regularly checking vital signs can help the patients to avoid serious health risks. Vital signs are the measurements and assessments of the critical functions of a living organism; considered as the first step for any clinical evaluation. Traditionally, the vital signs consist of temperature, pulse rate, blood pressure, and respiratory rate. Vitals indicate the inner condition of the body. The patient feeling fluctuations in the body, can take immediate action leading to successful treatments [4].

The academician and industrialists have been successful in developing smart plug and play energy-efficient components for dynamic environments. For such a smart component based dynamic systems, machine learning techniques are used along with the knowledge engineering and artificial intelligence [5], [6]. However, different data standards, data formats, machine languages, operating platforms knowledge management techniques and heterogeneous application [7] have made these systems very complicated. Moreover, all these factors are big obstacle in deploying and operating these systems in the dynamic environments because different data standards, application heterogeneity and the lack of uniform mark-up languages for sensor-based networks results in erroneous exchange of information among sensor devices. Additionally, systems operating in such environments also produce a lot of data continuously; for example, it is generally assumed that wearable devices of patients in an intensive care unit generates megabytes of data daily. The amount of data and the application heterogeneity highlights the need for automated data processing. In such dynamic environments medical staff must be supported through smart medical decision support systems [8].

With the advent of the semantic web, semantic technologies are increasingly being used to provide machine interpretation and processing capability to existing knowledge by overcoming the restriction of language and data heterogeneity [9], [10], [11]. Semantic web provides well-defined meaning to the knowledge which enables computers and people to work together to infer new knowledge with the help of intelligent reasoning engines and rules. Thus, semantic technologies create a universal medium for information exchange in a dynamic heterogeneous environment of devices by giving well-defined manning to the information in a machines processable way [4], [12]. This is a reason; researchers are doing their best efforts to use the potential of semantic technologies to deal with the data heterogeneity problems of IoT devices. The usage of autonomous reasoning in decision support systems, and mobile computing, provides cost-effective, and efficient patient care.

In this regard, Lopez et al. [5], have proposed an IoT-ontology enabled framework to monitor Corona patients which analyzes the sensor data like ECG, temperature, and accelerometer and starts an alarming in abnormal conditions to warn the people to adopt preventive measures; however, a little attention have paid on measuring the system performance and no mechanism is proposed to warn the remote healthcare professional. Similarly, Mutangadura [13], have proposed a Do-Care ontology-based monitoring system for chronically ill patients. Patients use wearable sensors which collect patient data and the Do-Care ontology reasoner by using Semantic Web Rule Language (SWRL) rules, determine the health of a patient. However, there is no support for doctors in preventive medication recommendations. Whereas, Sharma et al. [14], have proposed an ontology for patient knowledge repositories.

The ontology-based framework monitors and evaluates the vital signs of the patient. It also has the capability to automatically sense the geographical coordinates of patients to protect them from environmental hazards without the involvement of a medical professional. But this system uses a very limited number of ontological rules for decision making, resulting in a compromised decision-making process.

Indeed, all these [5], [13], [14], [37] studies emphasize on health-related IoT enabled ontology-based patient monitoring and treatment system. However, the main shortcoming in these systems is the lack of continuous updation of patients personalized information and a limited set of rules for inferencing the IoT data. Although, these systems focus on data modeling, data measurement, analysis, and decision making (limited) but overlook the agility and the performance of devices along with the security of data and the accuracy of decisions. Since, the system devices collect and transmit data. Therefore, the security of data must be ensured. In this regard, we have used the AES algorithm for the implementation of a lightweight cryptography on smartphones [38], [39].

Likewise, the quality of service can also play an important role in the healthcare system because it refers to the level of care and support provided by healthcare systems to the affected individual. For example in case of a emergencies, quality of service ensures that healthcare personnel are prepared to act promptly, providing immediate assistance to the patient. In such situations, response time (QoS) maters a lot in saving the life of the patient. Similarly, context awareness enables healthcare professionals to respond emergencies according to the specific circumstances and needs of the situation. It involves understanding the dynamic and evolving aspects of the emergency, including the location and severity.

The proposed system tracks the patient and records their health information. It has the capability to interact with the medical staff or caregiver to ensure timely intervention in case of an emergency. Moreover, patients may also receive online instruction to manage their health. In this regard, an ontology-based healthcare framework is used to organize the terms which describe the patients. The framework consists on a knowledge base to keep a record of personalized information of patients, and support the medical staff in decision-making with the help of reasoning rules, and to detect inconsistencies in the available data. The objective of this study is to:

- To develop a framework to capture sensor data and sharing patient information using semantic technologies.
- To support the medical staff in decision-making with automated reasoning rules to handle emergencies efficiently and effectively.

This work intends to answer the following questions:

- How do represent IoT devices and the relationship among them semantically?
- How do capture vital signs by using semantic relationships and using them in handling emergencies?
- How do facilitate the medical staff to process the data and use findings to treat a patient?

Our main contributions are as follows:

- Ontology-based intelligent patient monitoring healthcare framework.
- Ontology based reasoning rules for creating new knowledge.
- Remote patient monitoring ontology.
- Algorithms for the support of medical staff in decision making.
- Investigating the framework performance and accuracy with respect to human perception.

The paper is organized as follows. Section II, a review of related work is presented. Section III discusses the proposed ontology based patient monitoring IoT framework, and Section IV, provides the detail of ontology engineering process. In Section V, a mechanism for IoT device selection is presented. In Section VI, framework evaluation is performed and finally, Section VII concludes the work.

II. RELATED WORK

Recent advancements in sensor technologies are considered highly reliable for Healthcare Applications [17]. IoT based ontological solutions are emerging as promising enabling technologies to implement e-health [18]. Such solutions consists of multiple sensor nodes worn by patient that can measure and share patient's physiological state data through the ontological support with the healthcare professional [19].

In this regard, Sharma et al. [14], have proposed an IoT-based framework to monitor Corona patients. This framework consists of an ontology-based bio-wearable sensor for early detection of COVID-19 patients. Ontology-based remote monitoring system analyzes the sensor signals such as ECG, temperature, and accelerometer and starts an alarm to warn the people in the vicinity to adopt preventive measures. The authors have reported the 96.33% accuracy of the proposed model. They also observed that the proposed model is efficient in terms of power consumption. However, they have neither reported the simulation environment nor have quantified the power efficiency.

Elhadj et al. [15], have presented an ontology-based healthcare monitoring system (Do-Care) to monitor indoor as well as outdoor patients suffering from chronic diseases. The system uses wearable sensor devices to collect patient data. The proposed system uses Do-Care ontology reasoner which uses SWRL rules to determine the health of a patient in two states as Normal or Abnormal. However, the authors claim that system efficiency is tested but it has not been reported. Moreover, there is no mechanism to report the medical condition of the patient to the medical staff or caregiver.

Ajami and Mcheick [16], have proposed a framework that is based on the formal semantic standards for building an ontology knowledge repository. The framework is designed to monitor

patients' disease, location, activity, symptoms, risk factors, laboratory examination results, and treatment plans to provide ubiquitously personalized real-time medical care for COPD patients to reduce preventable harm. Framework monitors and evaluates the daily activities of the patient through scheduled events by adhering to the safe boundaries for the vital signs. To perform these tasks, the framework implements a set of ontologies along with a logical base of SWRL. The framework has the capability to monitor and control dynamic changes in physiological parameters intelligently to create safe ranges of vital signs of a patient. As the framework automatically senses the geographical coordinates of patients to protect them from environmental hazards without involving the medical professionals which might be dangerous and lethal.

Subramaniyaswamy et al. [40], have proposed a modified LWrE method. It is based on Somewhat Homomorphic Encryption Ring Learning with Error to protect patients' health information obtained from sensor-based devices. By the application of the proposed method, devices consume relatively less computing resources to encrypt and transmit data from edge devices to a cloud server. Singh et al. [41], have developed a LabVIEW based IoT model to detect the unbalanced input power supply during unsymmetrical power quality events. In such situations, the proposed model process the data immediately by limiting the storage space and ensuring the system responds efficiently. Resulting in reduced cloud storage space and increased response. The model provides the facility to access, analyze, store, and visualize information on different devices through the cloud-based IoT platform.

In order to predict patients health accurately from irregular Electronic Healthcare Records (EHR) data, Niu et al. [20], have proposed a Sequential visits and Medical Ontology (SeMO). The ontology learns medical concepts from sequential and irregular visits and predicts patient health with the help of ontological rules. To address the deficiency of sufficient information of patients, they proposed another model to fuse sequential visits and medical ontology to predict patients' death risk. They also introduced an attention mechanism in their model to improve the learning of the importance of features which improves the model performance. The author claims that the proposed model has

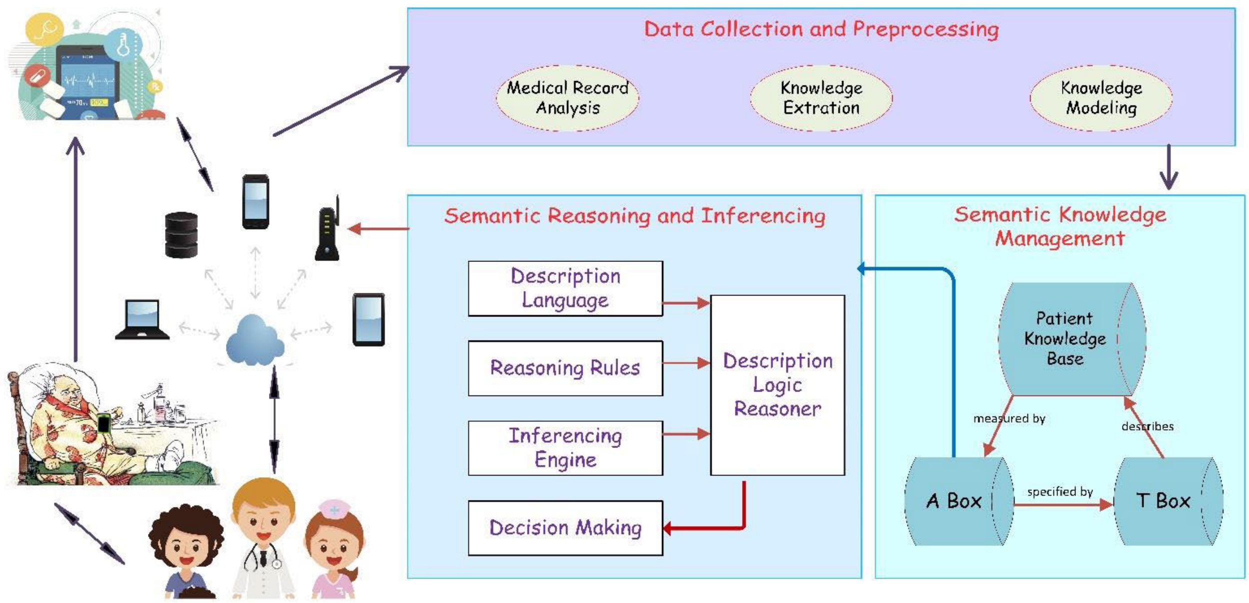

FIGURE 1. An IoT-enabled ontology-based Intelligent Healthcare Framework.

achieved precision up to 97%. However, this model does not consider the patient's profile and needs to be tested for accuracy and robustness.

Ali et al. [37], have proposed a smart healthcare monitoring framework for heart disease prediction using deep learning method. They used wearable sensors to collect data of the heart patients. To enrich the collected data before its used for prediction they used Framingham Risk Factors (FRFs) and feature fusion approach along with the information gain (IG) approach. Whereas, for diet recommendation SWRL rules are used. The proposed system has achieved an accuracy of 98.5% in heart disease prediction. Similarly, In another study [38], researchers proposed an ontology-based healthcare framework. Framework collects healthcare data (related to diabetes, BP, mental health, and drug reviews) from various sources like smartphones, wearable sensors, and social networks. To handle data inconsistencies, they used a big data analytics engine (based on bidirectional long short-term memory) and improved the data quality. While extracting valuable features from healthcare data and reasoning, they used.

Word2vec model along with the domain specific ontologies. Framework has the ability to classify patient health conditions and predicts drug side effects with an accuracy of 94%. El-Sappagh et al. [39], have proposed a model based on conventional ML techniques for the prediction of Alzheimer's disease progression. This model uses therapeutic chemical classification (ATC) ontology to represent drug names in a standard format. The model was trained and tested using a dataset of 1029 patients and achieved the performance of prediction with an accuracy of 90.51%, precision of 90.69%, recall of 90.51%, and F1-score of 90.41%.

Alahmar et al. [21], have proposed a framework for Clinical Pathways (guidelines of medical evidence). Clinical Pathways provides a well-defined approach for clinical guidelines implementation. The proposed system can work independently and can perform data analytics. The system also provides a decision-support strategy for the detection and treatment of diseases. In the framework, researchers have used ontologies for knowledge representation and sharing that makes the framework applicable to a specific Clinical Pathway. The researchers have strengthened their proposed Clinical Decision Support Systems by converting Clinical Pathways into ontology because ontology-based approaches provide a hierarchical architecture. Which helps the Clinical Pathway concepts to be modeled at the meta-level, that makes the framework practically applicable. They have implemented the proposed framework to demonstrate the reuse the Clinical Pathways of another hospital. They demonstrated this by linking it with the meta-ontology, and by modifying the Clinical Pathways.

Literature review reveals that almost all recent studies have adopted a knowledge-based approach, mainly relying on the semantic web where the healthcare frameworks are based on ontologies. The most common aspect in all frameworks is that they have focused on how to computerize healthcare-related IoT devices to improve the treatment of patients; therefore, exploring the effects of IoT ontology-based patient monitoring systems seems plausible. However, on the contrary to the above-discussed systems, researchers have focused on the integration of IoT devices for the collection and storing the data through ontologies and supporting decision-making processes by SWRL rules, along

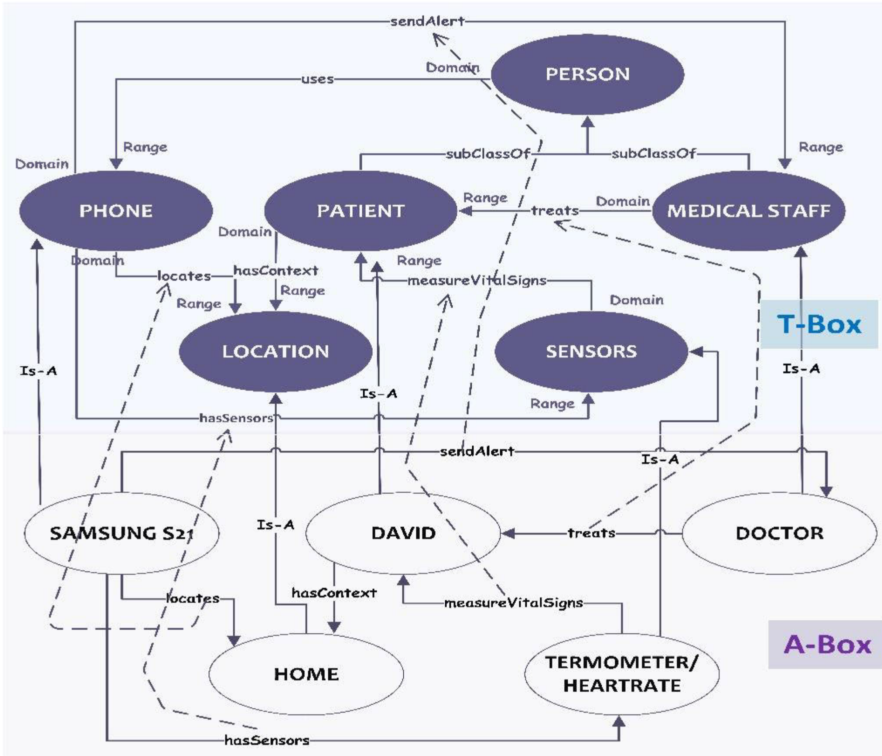

FIGURE 2. T-Box represents the terminological component while A-Box represent the assertional component of Patient Ontology.

with the sharing of information among other devices. This research proposes patient healthcare ontology to organize patient's information using a well-defined interoperable structure. The proposed ontology also serves the purpose of knowledge base for patient conditions, and also plays its role as a medical decision support tool that helps healthcare professionals to detect inconsistencies in the data of a patient.

III. FRAMEWORK PROPOSAL AND DESCRIPTION

To address the above-mentioned limitations, we initiated our work with the development of a robust ontological model, called PatientOntIoTFramework. The proposed framework is based on the ontology around which a smart environment and the core technology of IoT devices are shaped. The patient knowledge base store the data of patients in a machine-interpretable way. It also stores the logic of the data interpretation (just like the human brain organizes information) along with the categorization of classes, subclasses, relationships, instances, and the rules for the inferencing. After the design of ontological model, algorithms designing step was started to handle and to process the IoT device data. As the ontological model has to process data regularly and to share the processed information across diverse devices operating in different environments under the use of different people. Finally, for validation, the proposed model was deployed in a real-time environment. The framework consists of three main modules: Data collection and preprocessing (ontology engineering), semantic knowledge management, and semantic reasoning. A little but comprehensive detail of the framework (Figure 1) is given in the following subsections.

A. DATA COLLECTION AND PREPOSSESSING

The proposed framework has a patient knowledge base to store data of patients. Knowledge base consists of patient ontology, which organize patient data into information and knowledge by limiting complexity.; For example, from the sentences,

"Phone isA Device"
"Patient uses Phone"
"Phone hasA Sensor"
"Sensor measures VitalSign"
"TempSensor isA Sensor"
"TempSensor measure BodyTemperature"
"BodyTemperature hasMaxValue Interger"

"Phone, Sensor, VitalSign" are the concepts while *"isA, hasA, measure and uses"* are relations among these concepts whereas *"TempSensor"* is an instance of a sensor. Data collection and prepossessing functionality of the framework are discussed in detail in the ontology engineering section.

B. SEMANTIC KNOWLEDGE MANAGEMENT

Ontology-based knowledge representation (modeling using ontology markup languages) and reasoning make the computerized systems more intelligent that can infer conclusions and can make better decisions. In the context of the Semantic Web, Description Logic can be used to represent knowledge. The Description Logic knowledge base consists of a triple (T, A, R).

T (TBox) contains terminological axioms

A (ABox) contains assertional axioms

R (RBo) is a role box.

ABox describes the attributes of instances and the roles that is normally represented by an object diagram. ABox operations verify the correctness of instances and the consistency of ontology. Whereas, TBox statements are normally represented by a class diagram (showing associations, and generalizations). TBox (vocabulary of the domain) operations are responsible for inferencing. TBox and ABox are presented in Figure 2. Inference engines can perform deductive reasoning using TBoxe and ABox [50] to deduce things that are not directly defined in the ontological models.

Satisfiability: a concept C is satisfiable with respect to a TBox $\mathcal{T}$ iff there is an interpretation $\mathcal{I}$ of $\mathcal{T}$ such that $C^{\mathcal{T}} \neq \emptyset$. In TBox, MotherWithoutDaughter $\sqcap$ $\forall$ hasChild. Female is unsatisfiable.

Subsumption: a concept C is subsumed by a concept D with respect to a TBox $\mathcal{T}$ iff $C^{\mathcal{T}} \sqsubseteq D^{\mathcal{T}}$ for all interpretations $\mathcal{I}$ of $\mathcal{T}$. This can be denoted by $\mathcal{T} \models C \sqsubseteq D$. Example, Grandmother $\sqsubseteq_{\mathcal{T}}$ Mother.

Equivalence: a concept C is equivalent to a concept D with respect to a TBox $\mathcal{T}$ iff $C^{\mathcal{I}} = D^{\mathcal{I}}$ for all interpretations $\mathcal{I}$ of $\mathcal{T}$. This can be denoted by $\mathcal{T} \models C \sqsubseteq D$.

Disjointness: Two concepts C and D are disjoints with respect to a TBox $\mathcal{T}$ iff $C^{\mathcal{I}} \sqcap C^{\mathcal{I}} = \emptyset$ for all interpretations $\mathcal{I}$ of $\mathcal{T}$.

Reasoning tasks for ABox include:

Instance checking: An assertion α is entailed by $\mathcal{A}$, written $\mathcal{A} \models (\alpha)$, iff every interpretation that satisfies, that is, every model of $\mathcal{A}$, also satisfies α.

Realization: is consists on individuals along with a set of concepts; its task is to identify the specific concepts C in such a way that $\mathcal{A} \models C(\alpha)$; the most specific concepts are those that are minimal with respect to the subsumption ordering.

Retrieval: represents retrieval of all individuals of some concept, i.e. for a given concept C, compute the set $\mathcal{I}_{\mathcal{AT}}, (C)$ of individual names a used in $\mathcal{A}$ and satisfying $\mathcal{A} \models C(\alpha)$.

Knowledge base consistency: a knowledge base is consistent if there exists an interpretation TBox $\mathcal{I}$ that satisfies both $\mathcal{T}$ and ABox $\mathcal{A}$.

In **RBox**, Role statement represents the binary relationship among individuals. Moreover, R is a finite collection of generalized role inclusion axioms in the form of $R \sqsubseteq S$, $R \equiv S$ is a form of Role equivalence axiom while the complex role axiom is in the form of $R_1 \circ R_2 \sqsubseteq S$. However, in case of disjoint declarations axiom is in form $Dis(R, S)$ while in case of transitivity, $R^+ \sqsubseteq R$ is the axiom form where R^+ is a set of transitive roles and S is also a role.

C. SEMANTIC REASONING (DESCRIPTION LOGIC REASONER)

Rule-based systems can be used along with machine learning for decision making. However, rule–based systems lacks in awareness of their structure [22]; however, by combining rule-based system with ontologies; improves the self-awareness as well as the power of rules [23]. In this regard, the rule language proposed for OWL is the SWRL [24]. Below is a set of rules used by the proposed system to infer new knowledge while the graphical representation is presented in Figure 3.

Rule1: Patient(?p) ^MedicalStaff(?doc) ^uses(?p,?d) ^phone(?d,?ph) ^phoneStatus(?sat, ON) ^sendAlert(?ph,?doc) ^hasSensors(?ph,?sen) ^isTemperatureSensor(?sen,?temp) ^measureTemperatureOf(?temp,?p) ^hasTemperature(?p,? TempVal) ^swrl:greaterThanOrEqual(?TempVal,105) ^→ patientCondition(?ph, "Abnormal")

The above rule states if patients body temperature becomes equal or greater then 105F, then an alert message "abnormal" will be sent to the doctor.

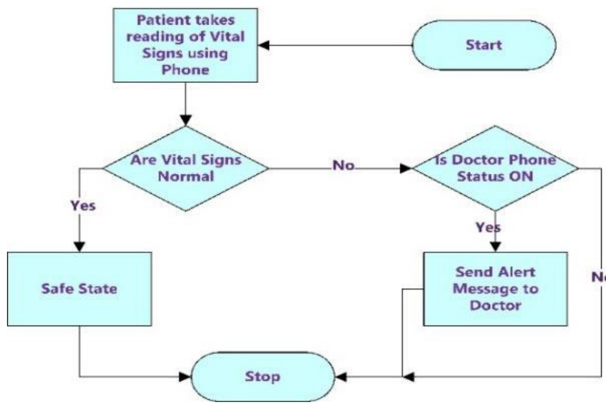

FIGURE 3. Rules-based emergency alert management at abstract level.

Rule2: Patient(?p) ^MedicalStaff(?doc) ^uses(?p,?d) ^phone(?d,?ph) ^phoneStatus(?sat, ON) ^hasBattery(?ph, ?bat) ^sendAlert(?ph,?doc) ^hasSensors(?ph,?sen) ^isTemperatureSensor(?sen,?temp) ^measureTemperatureOf (?temp,?p) ^hasTemperature(?p,? TempVal) ^swrl:lessThan OrEqual(?TempVal,90) ^swrl:greaterThanOrEqual(?bat,25) → patientCondition(?ph, "Abnormal")

The above rule states if patients body temperature becomes equal or less then 90F, then an alert message "abnormal" will be sent to the doctor.

Rule3: Patient(?p) ^MedicalStaff(?doc) ^uses(?p,?d) ^phone(?d,?ph) ^phoneStatus(?sat, ON) ^hasBattery(?ph, ?bat) ^sendAlert(?ph,?doc) ^hasSensors(?ph,?sen) ^isBP Sensor(?sen,?bpSen) ^

measureBloodPressueOf(?bpSen,?p) ^hasBP(?p,? bpSenVal) ^swrl:greaterThanOrEqual(?bpSenVal,120) ^swrl: greaterThanOrEqual(?bat,25)→ patientCondition(?ph, "Abnormal")

The above rule states if patients' blood pressure becomes equal or greater then 120, then an alert message "abnormal" will be sent to the doctor.

Rule4: Patient(?p) ^MedicalStaff(?doc) ^uses(?p,?d) ^phone(?d,?ph) ^phoneStatus(?sat, ON) ^hasBattery(?ph, ?bat) ^sendAlert(?ph,?doc) ^hasSensors(?ph,?sen) ^ isBPSensor(?sen,?bpSen) ^measureBloodPressueOf(?bpSen, ?p) ^hasBP(?p,? bpSenVal) ^swrl:lessThanOrEqual (?bpSenVal,90) ^swrl:greaterThanOrEqual(?bat,25)→ patientCondition(?ph, "Abnormal")

The above rule states if patients' blood pressure becomes equal or less then 90, then an alert message "abnormal" will be sent to the doctor.

Algorithm 1 Devices Suitability Calculation

***Input**: Devices*
***Output**: list of suitable devices in descending order(by score)*
for (α ∈ Di) ***do***
  if *(α.status="ON\" "&*
    α.batteryPower>thresholdValue) ***then***
  if *(α isQoSAttribute & Positive monotonic)* ***then***
    SQoS =1- ((Di value -α thresholdValue) / Di value)
  else if *(α isQoSAttribute & Negative monotonic)*
    then
      ScoreQoSList =1 / (1- ((Di value -α thresholdValue) / Di value))
    else if *(α isContextAwareAttribute) then*
    ParentNode = FindRoot (PatientOntTexnomy)
for *(PtrNode∈ ParentNdode)* ***do***
  if *(α semantically equal to PtrNode)* ***then***
    ContextAttributes (PtrNode)
    ScorecontextList = ContextAttributes (α) / ContextAttributes(PtrNode)
fore *(α ∈ScoreList)* ***do***
  DeviceScore =α ContextScore WD +α
    QoSscore WD
  ***Return** a list of Suitable Devices*

Rule5: Patient(?p) ^MedicalStaff(?doc) ^uses(?p,?d) ^ phone(?d,?ph) ^phoneStatus(?sat, ON) ^hasBattery(?ph, ?bat) ^sendAlert(?ph,?doc) ^hasSensors(?ph,?sen) ^isHBSensor(?sen,?bpSen) ^measureHeartBeatOf(?bpSen,?p) ^ hasHB(?p,? bpmVal) ^swrl:greaterThanOrEqual(?bpmVal, 190) ^swrl:greaterThanOrEqual(?bat,25)→ patientCondition (?ph, "Abnormal")

The above rule states if patients' heart beats becomes equal or greater than 190 per minutes, then an alert message "abnormal" will be sent to the doctor.

Rule6: Patient(?p) ^MedicalStaff(?doc) ^uses(?p,?d) ^phone(?d,?ph) ^phoneStatus(?sat, ON) ^hasBattery(?ph, ?bat) ^sendAlert(?ph,?doc) ^hasSensors(?ph,?sen) ^isHBSensor(?sen,?bpSen) ^measureHeartBeatOf(?bpSen,?p) ^ hasHB(?p,? bpmVal) ^swrl:lessThanOrEqual(?bpmVal,90) ^swrl:greaterThanOrEqual(?bat,25) → patientCondition (?ph, "Abnormal").

The above rule states if patients' heart beats becomes equal or less than 90 per minutes, then an alert message "abnormal" will be sent to the doctor.

D. DECISION-MAKING PROCESS

The proposed algorithms in this paper consider the context and QoS information for the calculation of the score to determine the best availabl device for communication. The similarity score depends on the semantic deviation between device attributes.

Once all the devices are compared and scored; the highest score device is selected for communication.

Elhadj et al. [15] have proposed a dynamic rule-based system. This system infers information and suggest medical recommendations based on the data of IoT devices. However, this work has three major problems: first, it does not consider the object and data properties of classes (nodes); second, it does not consider the ontology taxonomy for calculating score resulting in low precision of results; and, finally, it does not consider the value type directions (i.e. higher values are the best and vice versa). Following algorithms (Algorithm1 and Algorithm2) address these issues. Algorithm2 provides real-time alerting mechanism to rescue patients in abnormal situations. For example, in case, if patient body temperature increases by 40 °C. The patient condition is considered as abnormal, in this condition system sends to the device under the use of a person having the best score. The general procedure of alerting system is described by the Algorithm 1. Table 1 presents the ranges of vital signs according to the patient's age.

IV. ONTOLOGY ENGINEERING

Ontologies are considered one of the best ways of representing the machine processable knowledge [25] due to their ability to contain knowledge in a formal way, and their easy application in the medical decision support systems (based on reasoning processes) [21], [26]. The ontology introduced in this paper is for chronically ill patients whose concepts are finalized in consensus with domain experts. Ontology measures the vital signs of patients through the devices they use (e.g., mobile phone). However, for the development of this ontology, we considered the METHONTOLOGY [22] methodology from TOV, TERMINAE, SENSUS etc. because it is considered more formal than others. Moreover, its ontology development life cycle model (specification, conceptualization, formalisation, integration and finally implementation) is closer to the software development life cycle model. It can also be used for ontology reuse. The detail of ontology development steps is given below.

A. ONTOLOGY SPECIFICATION AND CONCEPTUALIZATION

Information extraction means extraction of information such as entities and relationships among them along with the attributes that are used to describe them. In the case

Algorithm 2 Emergency alert management

```
AlertNoticication (Emergency Alert)
Input: vital signs of patient and profile
Output: sending alert at a suitable device
DeviceList = SuitabilitDevice (List of AvailableDevices)
foreach (d ∈ DeviceList)
   if(d_responsTime > d.next_responsTime)
      d = d.next
end foreach loop
foreach (vs ∈ VitalSignsList)
      if (vs.temperature ≥ 37.5 or vs.temperature
   ≤ 36.5 & Patient.age≥ 18 or Patient.age≤ 65)
         d.sendAlert(Abnormal Temperature)
   if (vs.bloodPressure ≥ 120/80 or
   vs.bloodPressure ≤ 90/60 & Patient.age≥ 18 or
   Patient.age≤ 60)
         d.sendAlert(AbnormalBloodPressure)
   if (vs.heartRate ≥ 170 orvs.heartRate ≤ 100
& Patient.age≥ 18 or Patient.age≤ 30)
         d.sendAlert(Abnormal Heart Rate)
   if (vs.heartRate ≥ 153 orvs.heartRate ≤ 90 &
Patient.age≥ 31 or Patient.age≤ 40)
         d.sendAlert(Abnormal Heart Rate)
   if (vs.heartRate ≥ 170 orvs.heartRate ≤ 100 &
Patient.age≥ 41 or Patient.age≤ 50)
         d.sendAlert(Abnormal Heart Rate)
   if (vs.heartRate ≥ 145 orvs.heartRate ≤ 85 &
Patient.age≥ 51 or Patient.age≤ 60)
         d.sendAlert(Abnormal Heart Rate)
      if (vs.heartRate ≥ 70 orvs.heartRate ≤ 60 &
   Patient.age≥ 61 or Patien t.age≤ 70)
         d.sendAlert(Abnormal Heart Rate)
end foreach loop
```

of medical domain, medical staff has a huge amount of information (tacit knowledge). The big challenge for us was how to identify and extract this information. During this step (concept identification), we interviewed domain experts along with reviewing relevant scientific work [27], [28], [29]. We used the weighting technique (equation 1) during the collection of concepts, according to the technique, with the repetition of each concept, the score of the concept is increased by one. Finally, above-average concepts were selected with the consultation of domain experts.

$$AverageScore = \frac{\Sigma ConceptScore}{\Sigma Concepts} \tag{1}$$

A taxonomy formalizes the hierarchical relationships among concepts and specifies the term to be used to refers to each other. Taxonomy prescribes structure and terminology in a tree-like structure (classify a set of things). Moreover, taxonomies provide a common point of view of classes, subclasses and the relationship among them, it is also considered as the backbone of the ontology [30]. A taxonomy for patient ontology is presented in Figure 4.

Ontology servers the purpose of specifying the metadata. Whereas the metadata characterizes the conditions under which ontological data can be shared and reused. It means that ontology includes the vocabulary along with the intended interpretations. Figure 5 presents the core structure of internal ontology with relations.

Visual Notation (VOWL) provides graphical representation of ontology elements. It is used to visualize classes and individuals of the represented ontology with the help of different colors. With the help of colors, it becomes easy to understand the relations between the elements of the ontology along with the help of developers to encode the semantics [31].

Figure 6 presents the properties of ontology that are used as a predicate in statements to describe individuals. There are two major types of properties; first, object properties (Table 2) to link individuals to other individuals, and second, the data properties (Table 3) to link individuals to literal values. OWL and RDFS gives expressive vocabulary to develop expressive and rigorous data models. Moreover, OWL allows to tailor the said computational realities and application requirements, such as queries, rules, policy enforcement, etc. Therefore, few object properties of the patient ontology are presented below in the form of RDFs syntax.

TABLE 1. Object properties from patient ontology.

Object Property	Domain	Range	Property Characteristics
hasA	Phone	Sensor	Functional
hasA	Person	Profile	Functional
hasA	Phone	LocationSensor	Functional
measure	Sensor	VitalSigns	Functional
send	Phone	AlertMessage	Functional
use	Person	Phone	Functional
hasA	Person	Age	Functional
hasDateTime	Sensor	TimeStamp	Functional

```
////////////////////////////////////////////////////////////////////////////
// Object Properties //
////////////////////////////////////////////////////////////////////////////
   <ObjectProperty rdf:about="Ont:hasA">
   <rdfs:domain rdf:resource="Ont:Person"/>
<rdfs:range rdf:resource="Ont:Profile"/>
</ObjectProperty>
<ObjectProperty rdf:about="Ont:use">
   <rdfs:domain rdf:resource="Ont:Person"/>
   <rdfs:range rdf:resource="Ont:Phone"/>
</ObjectProperty>
<ObjectProperty rdf:about="Ont:hasA">
   <rdfs:domain rdf:resource="Ont:Phone"/>
   <rdfs:range rdf:resource="Ont:Sensor"/>
</ObjectProperty>
<ObjectProperty rdf:about="Ont:measure">
   <rdfs:domain rdf:resource="Ont:Sensor"/>
   <rdfs:range rdf:resource="Ont:VitalSigns"/>
```

```
</ObjectProperty>
<ObjectProperty rdf:about=“Ont:send″>
   <rdfs:range rdf:resource=“Ont:AlertMessage″/>
   <rdfs:domain rdf:resource=“Ont:Phone″/>
</ObjectProperty>
```

A data property is relationship between ontological instance and some literal. These properties can be arranged in a sub-property hierarchy. Since these properties have domains and ranges, so these can be used to create property restrictions. Data properties of patient ontology are presented in Table 2. A few data properties of the patient ontology are presented below in the form of RDFs syntax. Individuals are known as instances (base unit of an ontology).

TABLE 2. Data properties from patient ontology.

Data Property	Domain	Range
AlertMessage	Alert	String.
hasAddress	Address	String.
hasAge	Age	Float
hasGender	Person	String.
hasMax_bpm	Patient	Integer.
hasMin_bpm	Patient	Integer.
hasMax_mmHg	Patient	Integer.
hasMin_mmHg	Patient	Integer.
hasMaxTemperature	Patient	Integer.
hasMinTemperature	Patient	Integer.
hasName	Person	String.
hasPhoneNumber	Person	String.
personId	Person	String.

Individuals can be used to model the concrete objects such as patients and devices. Individuals may also model more abstract objects such as patient profile.

```
///////////////////////////////////////////////////////////////////////////
// Data properties //
///////////////////////////////////////////////////////////////////////////
<DatatypeProperty rdf:about=“Ont:hasAddress″>
   <rdfs:domain rdf:resource=“Ont:Person″/>
<rdfs:range
 rdf:resource=“http://www.w3.org/2001/XMLSchema
#string″/>
</DatatypeProperty>
<DatatypeProperty rdf:about=“Ont:hasAge”>
   <rdfs:domain rdf:resource=“Ont:Person″/>
   <rdfs:range
    rdf:resource=“http://www.w3.org/2001/XMLSchema
   # integer″/>
</DatatypeProperty>
<DatatypeProperty rdf:about=“Ont:hasMax_bpm″>
   <rdfs:domain rdf:resourcez“Ont:PulseOximeter″/>
   <rdfs:range
    rdf:resource=“http://www.w3.org/2001/XML
   Schema# integer″/>
</DatatypeProperty>
<DatatypeProperty rdf:about=“Ont:hasUnit″>
   <rdfs:domain rdf:resource=“ Ont:PulseOximeter″/>
   <rdfs:range
    rdf:resource=“http://www.w3.org/2001/XMLSchema
   # string″/>
</DatatypeProperty>
```

Individuals are a formal part of an ontology used to describe the entities of interest. A few individuals of the patient ontology are presented below in the form of RDFs syntax.

```
<!– //////////////////////////////////////////////////////////////////////
// Individuals //
////////////////////////////////////////////////////////////////////// –>
<NamedIndividual rdf:about=“Ont:David-Patient″>
   <rdf:type rdf:resource=“Ont:Patient″/>
   <untitled-ontology-3:hasProfile
   rdf:resource=“Ont:D_Profile″/>
   <untitled-ontology-3:use
   rdf:resource=“Ont:Samsung_S21″/>
</NamedIndividual>
<NamedIndividual
rdf:about=“Ont:Samsung_S21″>
   <rdf:type rdf:resource=“Ont:Phone″/>
   <untitled-ontology-3:send
   rdf:resource=“Ont:AlertMessage″/>
   <untitled-ontology-3:hasSensor
   rdf:resource=“Ont:Sensor_BP″/>
   <untitled-ontology-3:hasSensor
   rdf:resource=“Ont:Sensor_HeartBeat″/>
   <untitled-ontology-3:hasSensor
   rdf:resource=“Ont:Sensor_Location″/>
   <untitled-ontology-3:hasSensor
   rdf:resource=“Ont:Sensor_Temprature″/>
</NamedIndividual>
<NamedIndividual rdf:about=“Ont:D_Profile″>
   <rdf:type rdf:resource=“Ont:Profile″/>
   <untitled-ontology-3:hasPhoneNumber
   rdf:datatype=“& xsd;string”> +0014321</
   untitled-ontology-3:hasPhoneNumber>
   <untitled-ontology-3:personID
   df:datatype=“&xsd;string”>123</untitled-
   ontology-3:personID>
   <untitled-ontology-3:hasAge
   rdf:datatype=“&xsd;integer”>45</untitled-ontology-
   3:hasAge>
   <untitled-ontology-3:hasName
   rdf:datatype=“&xsd;string”>David</untitled-
   ontology-3:hasName>
   <untitled-ontology-3:hasAddress
   rdf:datatype=“&xsd;string”>House 184
   Lahore</untitled-ontology-3:hasAddress>
   <untitled-ontology-3:hasGender
   rdf:datatype=“&xsd;string”>Male</untitled-
   ontology-3:hasGender>
</NamedIndividual>
```

B. GRAPHICAL REPRESENTATION OF ONTOLOGY

Ontologies visualization means viewing the information graphically. Ontology visualization makes it easier for experts and non-experts to identify inconsistencies and errors

FIGURE 4. **The structural aspect of the proposed ontology.**

in the ontology. The identification of errors help the ontology developers to rectify them before their real implementation in the environment. Which results in correct decision-making; this is particularly important in situations where ontology might have different aspects. In this regard, OntoGraph is one of the tools used to visualize an ontology [32]. OntoGraph is used to visualize ontology as a graph, where nodes represent concepts with edges representing relationships. Moreover, it also helps the stakeholders to navigate the ontology graph interactively through its visual interface and retrieving details of ontology concepts and relationships. Moreover, OntoGraph also provides functionality to visualize relationships between concepts in a hierarchical way. Figure 7 shows the OntoGraph of our ontology.

C. SPARQL QUERY RESULTS

SPARQL is the standard query language and protocol (the only semantic query language) compliant with the W3C) designed to query data, and extract information hidden in the RDF data. It can navigate the relationships in RDF data through graph pattern matching. SPARQL queries not only match patterns but also have a wide range of mathematical operations to use for creating filters and new variable bindings. Before querying the ontology, First, ontology consistency checking will be performed, if the ontology will be consistent then the query will be executed otherwise an error message will be returned.

PREFIX rdf: < http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: < http://www.w3.org/2002/07/owl#>
PREFIX xsd: < http://www.w3.org/2001/XMLSchema#>
PREFIX rdfs: < http://www.w3.org/2000/01/rdf-schema#>
PREFIX Ont: < http://www.semanticweb.org/cui/ontologies/2022/7/untitled-ontology-3#>

SELECT distinct ?Patient ?Profile ?Phone ?PhoneNumber ?Address ?Name ?Age ?Location ?Gender

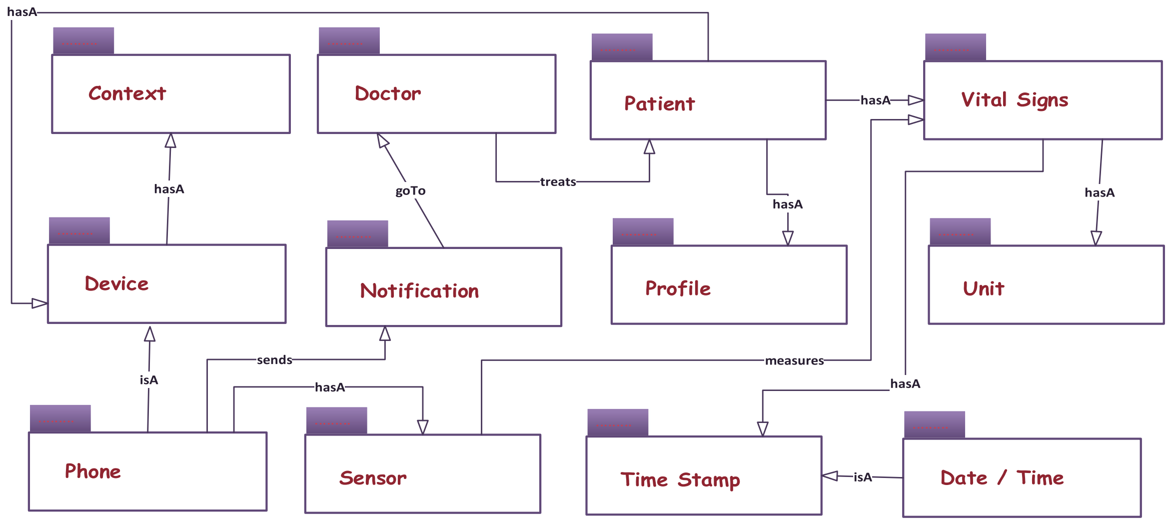

FIGURE 5. **Core structure of the proposed patient ontology.**

WHERE {
?Patient Ont:use ?Phone.
?Patient Ont:hasProfile ?Profile.
?Profile Ont:hasPhoneNumber ?PhoneNumber.
?Profile Ont:hasAddress ?Address.
?Profile Ont:hasName ?Name.
?Profile Ont:hasAge ?Age.
?Profile Ont:hasGender ?Gender.
?Phone Ont:hasSensor ?Sensor.
?Sensor rdf:type ?PhoneLocationSensor.
?Sensor Ont:hasLocation ?Location.
}

SPARQL query enables users to query information from data source that can be mapped to RDF. RDF entities can be identified by Universal Resource.

Identifiers (URIs) which allows data to be unambiguously referenced across different platforms. In the triple pattern (subject, predicate and object) of SPARQL query, each element can be a variable. SPARQL is declarative language recommended by W3C for RDF graphs which provide the pattern matching facility during searching and extraction of knowledge. The graphical representations of the above SPARQL query are presented in Figure 8.

PREFIX rdf: < http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: < http://www.w3.org/2002/07/owl#>
PREFIX xsd: < http://www.w3.org/2001/XMLSchema#>
PREFIX rdfs: < http://www.w3.org/2000/01/rdf-schema#>
PREFIX Ont: < http://www.semanticweb.org/cui/ontologies/2022/7/untitled-ontology-3#> SELECT ?Patient ?Profile ?Address ?SensorType ?Unit ?MaxHeartRate ?MinHeartRate
WHERE *{*
?Patient Ont:hasProfile ?Profile.
?Profile Ont:hasPhoneNumber ?PhoneNumber.
?Profile Ont:hasName ?Name.
?Profile Ont:hasAddress ?Address.
?SensorType Ont:hasMeasurementUnit ?Unit.
?SensorType Ont:hasMax_bpm ?MaxHeartRate.
?SensorType Ont:hasMin_bpm ?MinHeartRate.
FILTER (?PhoneNumber = "+0014321")
}

The above query returns the results of heartbeat rate (maximum & minimum) while the following query finds the results of blood pressure of the patient and send these results along with the body temperature to the description logic reasoner which decides the patient condition as normal or abnormal by using SWRL rules.

PREFIX rdf: < http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: < http://www.w3.org/2002/07/owl#>
PREFIX xsd: < http://www.w3.org/2001/XMLSchema#>
PREFIX rdfs: < http://www.w3.org/2000/01/rdf-schema#>
PREFIX Ont: < http://www.semanticweb.org/cui/ontologies/2022/7/untitled-ontology-3#> SELECT ?Patient ?Profile ?Address ?SensorType ?Unit ?BloodPressure
WHERE {
?Patient Ont:hasProfile ?Profile.
?Profile Ont:hasName ?Name.
?Profile Ont:hasPhoneNumber ?PhoneNumber.
?Profile Ont:hasAddress ?Address.
?SensorType Ont:hasMeasurementUnit ?Unit.
?SensorType Ont:hasMax_mmHg ?BloodPressure.
FILTER (?PhoneNumber = "+0014321")
}

The results are then sent to the decision-making component of the semantic reasoning engine of the proposed framework for further processing.

V. DEVICE SELECTION FOR NOTIFICATION

endenumerate The proposed framework categorizes patient monitoring process into five major subprocesses described

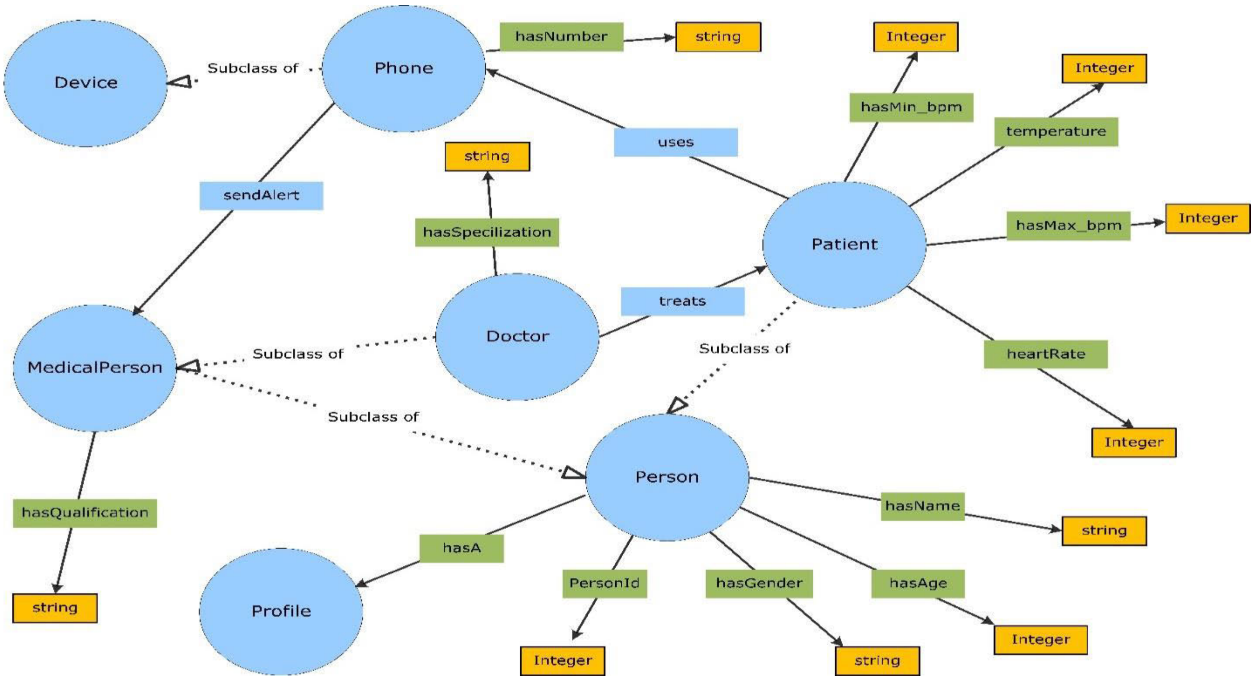

FIGURE 6. **User-oriented representation of patient ontology using VOWL plugin.**

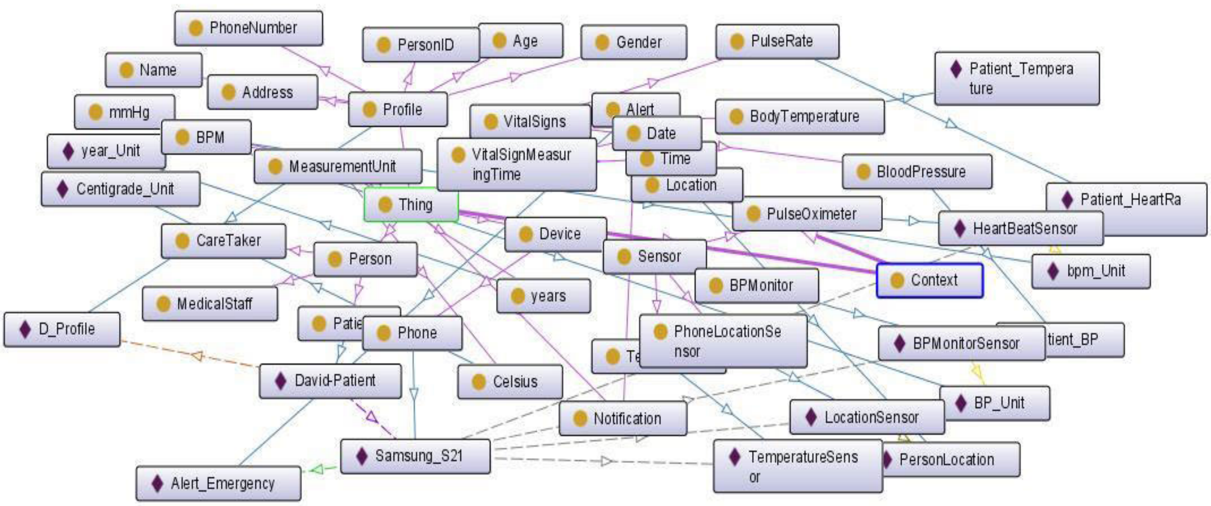

FIGURE 7. **OntoGraph of patient ontology in Protégé editor.**

in the ontology as five general classes: context information, patient, and caregivers along with their profiles, sensors, body vital sign measurement and alert management.

In the framework patient take measure vital signs of his body through phone sensors, the application processes the information and in case of abnormal readings, phone sends alert to the caregiver and the medical staff based on the context awareness (location) and QoS attributes of the devices used by people. As discussed above application select the device with less response time and with batter battery level and near to the patient. The process of context-awareness matching and QoS calculation is explained in the following subsections.

A. CONTEXT AWARENESS

The context of any device is defined by its location, and status etc. To determine the closeness between the location of the patient and the location of the caregiver's device; the subsumption relation between these two devices can be compared by the following rules. These rules were proposed

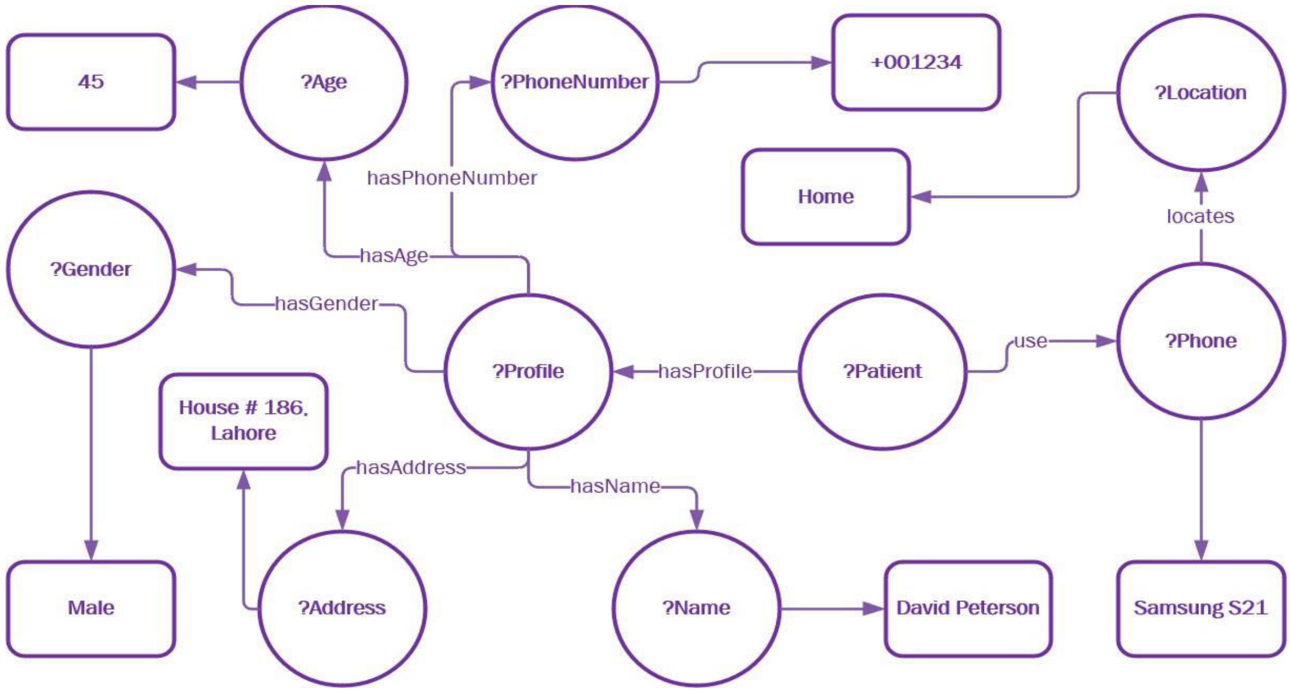

FIGURE 8. Graphical representation of SPARQL query results.

by Tan et al. [33]; however, he has not considered the ontology taxonomy levels which compromises the accuracy of context matching. Therefore, keeping in view these limitations the modified rules are presented below.

$$\begin{aligned}
&ContxAwareMatch(PD, MD) = (PD = MD) \vee (PD \subseteq MD) \\
&\quad \vee (PD \subseteq PD) \\
&Where(PD = MD) = (PD.IsStringConcept \\
&\wedge MD.IsStringConcept) \wedge (PD.value = MD.value) \\
&(MD \subseteq PD) = (PD.IsStringConcept \wedge MD.IsStringConcept) \\
&\wedge (PD.level \leq MD.level) \\
&(PD \subseteq MD) = (PD.IsStringConcept \wedge MD.IsStringConcept) \\
&\wedge (PD.level \geq MD.level) \qquad (2)
\end{aligned}$$

The context concepts can be either named or numbers [34]. If the context concepts of devices (in case of a named concept) are in the same branch of taxonomy tree, then its score will be calculated using the following formula:

$$\begin{aligned}
&LevelPD.Context = \sum Level(PD.context) \\
&LevelMD.Context = \sum Level(MD.context) \\
&IfLevel(MD.context) >= Level(PD.context) \\
&Dscore = (LevelPD.Context / LevelMD.Context) * W) \qquad (3)
\end{aligned}$$

where PD represents the patient device and MD represents the caregiver's device. D_{score} denotes the total score of a device.

B. QoS SCORE CALCULATION

Rules for QoS score calculation were proposed by Kritikos, and Plexousakis [34] but they have not considered weighting technique for QoS metric concepts for while calculating QoS score. The weighting technique for QoS metric concept is important because if a patient is in critical condition then application must send alert to the low response device (weight must be given to the less responding device) however, if its battery power is about to nil then the importance must the given to the device having batter battery level although have comparatively higher response time.

QoS metric concepts can either be positive or negative monotonic. In case of high values are preferred (positive monotonic), the score of the concept will be calculated by equation 4.

$$MDQoSscore = \frac{MDvalue - DthresholdValue}{MDvalu} \qquad (4)$$

Otherwise, the score of the concept will be calculated through equation 5.

$$MDQoSscore = \frac{1}{1 - ((MDvalue - DthresholdValue)/MDvalue)} \qquad (5)$$

While equation 6 calculates the total score of metric.

$$FinalScore = \sum (MD_{score}\, W + MD_{QoSscore}\, W) \qquad (6)$$

W_D is the weight of the QoS attribute.

VI. EVALUATION

In this section, the experimental evaluation of the proposed technique is performed. In this regard, we have examined a small set of 10 patient's data (selected randomly just to maintain the simplicity) from a large pool of patient data. The proposed patient ontology was populated with data using Protégé editor before performing reasoning to deduce new knowledge [35]. Which was used for assessing the patient's condition and the recommendations.

To understand the working of the proposed system, following scenario may be considered.

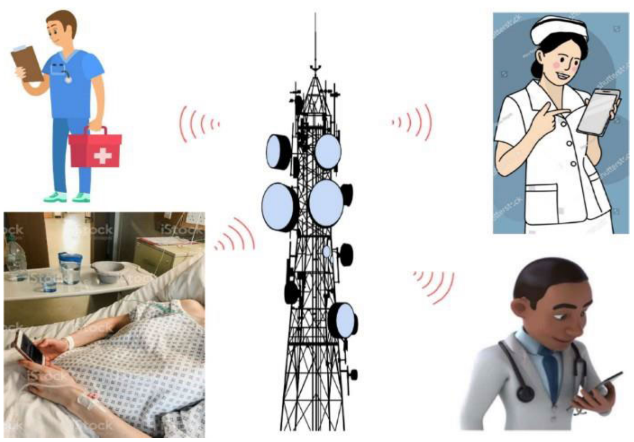

FIGURE 9. Use case scenario of IoT devices in healthcare.

Patient using phone measure his vital signs frequently, if the reading exceeds the threshold values, the proposed system becomes activated. Sample data of two patients is presented in Table 4 to demonstrate the application of the proposed framework.

TABLE 3. Patient vital signs.

	Age	Body Temp.	Blood Pressure Max	Blood Pressure Min	Heart Beat	Location
Patient A	55	39	128	82	89	Home
Patient B	72	37	108	68	120	Home

The application, process the data with the help of ontology and for decision making (Figure 9), the application uses two algorithms; first Algorithm 1, check the available devices (ON status) and then calculates the quality-of-service score of each device. Finally, this algorithm sort the devices based on the total score in a descending order. During score calculation Algorithm 1, by default gives the highest weight to the response time of the devices which mean that person using the device with least response time is the nearest to the patient and can reach immediately to the patient. Whereas, the Algorithm 2, send patients abnormal condition alert to the person using device having low response time; however, before sending message this algorithm verifies the vital signs threshold values again which were previously concluded by the inference engine.

OWL is a semantic markup language for publishing and sharing ontologies on the World Wide Web. OWL DL [36], a particular version of OWL, famous for the maximum expressiveness by maintaining computational completeness and decidability is used by the proposed application.

The DL descriptions of few devices is given below.

Device1≡ Phone⊓ (∃isUsedBy.Person⊓ Person(Doctor) ⊓ ∃hasBatteryPower.BatterValue ⊓ ∃has.Status⊓

Status (Off)⊓ ∃has.Location⊓ Location(Home)⊓ (=85has BatterValue)⊓ ⊓ (=.33hasResponseTime)

Device2≡ Phone⊓ (∃isUsedBy.Person⊓

Person(Paramedical)⊓ ∃hasBatteryPower.BatterValue ⊓ ∃has.Status⊓ Status (On)⊓ ∃has.Location⊓ Location(Clinic) ⊓ (=55hasBatterValue)⊓ (=0.45hasResponseTime)

Device3≡ Phone⊓ (∃isUsedBy.Person⊓ Person(Doctor) ⊓ ∃hasBatteryPower.BatterValue ⊓ ∃has.Status⊓ Status (On)⊓ ∃has.Location⊓ Location(Hospital)⊓ (=20hasBatter Value)⊓ (=0.25hasResponseTime)

Device4≡ Phone⊓ (∃isUsedBy.Person⊓ Person(Doctor)⊓ ∃hasBatteryPower.BatterValue ⊓ ∃has.Status⊓ Status (Off) ⊓ ∃has.Location⊓ Location(Home)⊓ (=75hasBatterValue) ⊓ (=0.30hasResponseTime)

Device5≡ Phone⊓ (∃isUsedBy.Person⊓ Person (Paramedical)⊓ ∃hasBatteryPower.BatterValue ⊓ ∃has.Status ⊓ Status (On)⊓ ∃has.Location⊓ Location(Home)⊓ (=65has BatterValue)

⊓ (=0.41hasResponseTime)

The human understandable format of above-described devices are presented in Table 5. Medical device having low response time means medical staff person using that device is near to the patient. Moreover, it is assumed that if the medical person is at home, it means that he can attend patient easily because (s)he is not busy at his workplace. Therefore, for the medical person selection to respond the patient following criteria was set by domain experts.

TABLE 4. Medical staff's device data.

ID	Medical Staff	Phone Battery	Phone Status	Context (Location)	Response Time (sec)
D1	Doctor	85	Off	Home	0.33
D2	Paramedical	55	On	Clinic	0.45
D3	Doctor	20	On	Hospital	0.25
D4	Doctor	75	Off	Home	0.30
D5	Paramedical	65	On	Home	0.41
D6	Doctor	18	On	Hospital	0.25
D7	Nurse	69	On	Home	0.37
D8	Paramedical	35	Off	Clinic	0.42
D9	Doctor	27	On	Hospital	0.25
D10	Nurse	58	Off	Clinic	0.36

First, device status should be "ON"; Device response time should be the lowest; Location "home" is preferred; doctor as a medical staff is appreciated; however, if doctor is not available then paramedic and nurse are preferred respectively. Similarly, in case of location, a medical staff at home can reach easily to the patients because he has no job restrictions, whereas job for a medical person working at clinic are comparatively less than to a person working at a hospital. In addition, device battery full is recommended or at least must be more than 20% and finally device response time 0.01 is considered as very good. Upon request to assign weights quantitatively to the said criteria; domain experts assigned weights: Response time = 0.4; Medical staff = 0.3 (0.2+0.06+0.04); Battery power = 0.2; Location = 0.1(0.05+0.03+0.02). Similarly, group criteria weights are as: QoS = 0.6 and Context-Awareness = 0.4.

While explaining the weights assigned, experts briefed that in emergency, the response time is the most important factor. Moreover, it might be assumed that if the response time of a device is low, it means that the person using that device is nearby. This is a reason they have assigned the highest weight to the response time and least to the location. Similarly, a doctor can handle emergency in a much better way than anyone else. That is why they assigned higher weight as compared to the battery power of the device.

A. RESULTS AND DISCUSSION

The proposed patient monitoring framework is based on the ontology that uses SWRL rules at the initial stage to conclude the normal/abnormal position of patients upon capturing and processing data. If SWRL rules conclude that the patient's condition is serious; second phase of the framework become activated to find the most suitable device based on its user profile, context-awareness, and quality of service attributes. In Table 5, score of devices are calculated according to the guidelines of the second phase to reach the conclusion.

TABLE 5. Score computation of attributes of devices.

ID	Medical Staff	Phone Battery	Phone Status	Location	Response Time (sec)	Total Score
D1	0.200	0.150	0	0.050	0.260	0.660
D2	0.060	0.130	1	0.018	0.360	1.568
D3	0.200	0.000	1	0.012	0.200	1.412
D4	0.200	0.150	0	0.050	0.240	0.640
D5	0.060	0.140	1	0.050	0.330	1.580
D6	0.200	-0.020	1	0.012	0.200	1.392
D7	0.040	0.140	1	0.050	0.300	1.530
D8	0.060	0.090	0	0.018	0.340	0.508
D9	0.200	0.050	1	0.012	0.200	1.462
D10	0.040	0.130	0	0.018	0.290	0.478

Table 5 presents the computed score of the proposed approach implemented in eclipse editor (Figure 10) using Apache Jena (an open source Semantic Web framework).

Device properties presented in Table 5 can be categorized into two groups: Context-aware attributes and QoS attributes. For both type of categories different score calculation methods are used (as described in section V-A and V-B). Context attributes are medical staff, phone status and location while QoS attributes are battery power and response time. The context-aware score and QoS score of devices are presented in Figure 11 by excluding the score of phone status, which is either 0 or 1, whereas the remaining attributes carry values

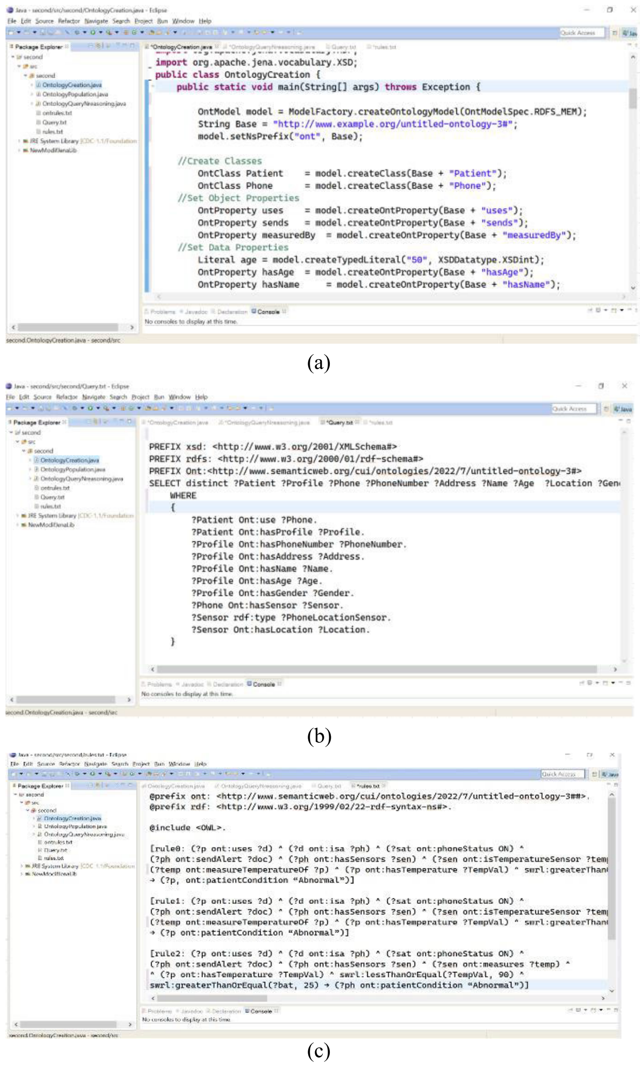

FIGURE 10. (a). Ontology populating with data using Jena with eclipse. (b). Jena SPARQL implementation to query an ontology in eclipse. (c). Reasoning ontology in eclipse using Jena.

between 0 and 1. Moreover, to make the comparison realistic, two attributes of each category are considered. By computing score of each category, it is observed that there is no big difference between the scores of context-awareness and QoS attributes of devices that are 0.31 and 0.36, respectively.

Since context attributes are name concepts therefore their similarity is calculated through taxonomy using equations 2 and 3.

Whereas, battery power and response time are number attributes so, their similarity is calculated through equation 4 and 5. Finally, the total score of context aware and QoS attributes while considering the user defined weight is calculated by equation 6. For example, the first instance of first the attribute of device 1 (D1 in Table 5) is context attribute so, its similarity score is calculated through taxonomy (Figure 4); on the taxonomy this concept along with other concepts resides on the same level so, its score is one. By multiplying this score to its weight (0.2) the total

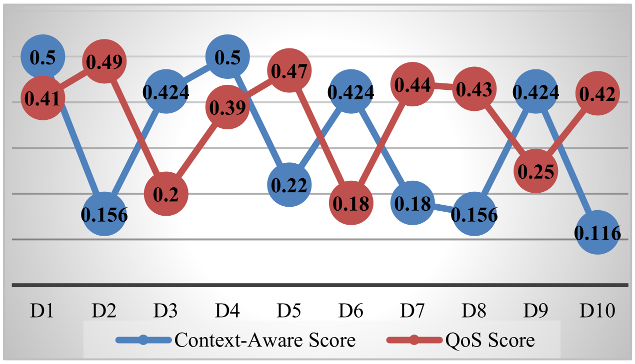

FIGURE 11. Context-aware and QoS score comparison.

score for this particular concept is computed which is 0.2, presented in Table 6 against the device 1 (D1) in the first column. Similarly, third (phone status) and fourth (location) attributes are also context attributes so, their scores are also calculated in the similar fashion. For third attribute the score is considered 1 if the status is on otherwise 0; whereas for the fourth attribute (location), the concept (home) is mapped on taxonomy to calculate its level which is 3. Since preferred value of the concept is also home therefore, the computed value is 1. By multiplying this value with its weight (0.05) the final score of the attribute is calculated and presented in Table 6. However, attributes two and five are QoS concepts in Table 5 and 6; therefore, their value is calculated in a different way. For example, second attribute of D1 (phone battery) in Table 5 is a QoS attributes and a positive monotonic therefore, its value is calculated with the help of equation 4. Whereas, fifth attribute (response time) is a negative monotonic thus its value is calculated with the help of equation 5. However, the total score of device (D1) is calculated while considering the group weights of context awareness and QoS with the help of equation 6.

By evaluating the results described in Table 6, it is observed that devices from most suitable to least are as: D5, D2, D7, D9, D3, D6, D1, D4, D8, and D10. This mean that in emergency, a person using device 5 is the most suitable person who can reach the patient easily whereas person 2 is the next and then person 7. These results are drawn based on the score calculated using context-awareness and quality of service of devices. In context-awareness priority is given to doctor over paramedics and nurses whereas in quality of service, priority is given to the response time over device battery. Figure 11 describes the context aware and QoS score comparison. From this graph it is observed that there are steady rise and fall in the device quality of service attributes whereas a very sharp fluctuation in the context score. By analyzing these trends, it is observed that a sharp rise and fall in context score is due to the 1) device status which is either on or off, contributing absolute values in the score. For example, in case of ON score rises by 1 while in case of OFF, score decreases by one. Whereas, in rest of cases, score increases or decreases in points.

B. EVALUATION BY EXPERTS

In order to know that how much the proposed system have ability to produced results near to the human perception; a survey was conducted. For the survey, we selected the participants with at least 16 years of education, with at least one year of experience of development or of quality assurance of applications in the medical domain.

The Table 5 with additional column for marks and with an extra space for comments along with all necessary instructions was presented to the participants. Participants were asked to assign a number between 1 to 10 for each to be considered for the treatment of the patient. They were requested to give highest marks to the most suitable device and lowest to the least appropriate one. Survey was distributed among 120 participants. Eighty (80) responses were collected in which 47 were complete and carefully filled. Among 47, 10 are displayed in Table 7. These ten responses were randomly selected.

TABLE 6. Survey results.

ID	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	Avg
D1	0	0	0	0	0	0	0	0	0	0	0.0
D2	8	10	6	6	8	8	8	10	6	6	7.6
D3	6	9	7	8	5	8	6	8	7	8	7.2
D4	0	0	0	0	0	0	0	0	0	0	0.0
D5	9	7	8	7	9	10	9	7	9	7	8.2
D6	5	6	5	5	6	7	5	5	5	5	5.4
D7	10	9	9	10	10	6	10	9	10	10	9.3
D8	0	0	0	0	0	0	0	0	0	0	0.0
D9	7	5	10	9	7	5	7	6	8	9	7.3
D10	0	0	0	0	0	0	0	0	0	0	0.0

By evaluating the survey results described in Figure 12, experts have concluded that (based on the average score) person using device D7 is the most suitable to treat a patient followed by person using devices D5, D2, D9, D3 and so on.

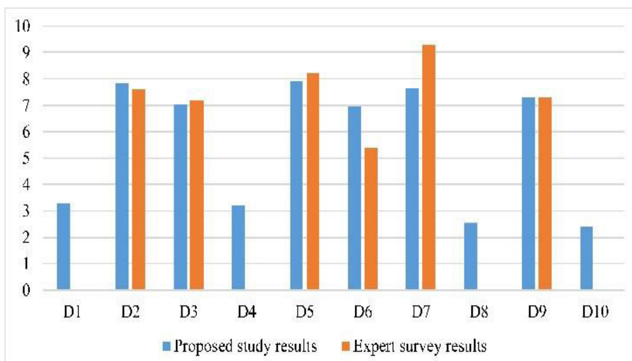

FIGURE 12. Comparative evaluation of results of proposed approach and the results of expert survey.

By carefully analyzing the first 50% results produced by the proposed framework and by the human; it is observed that first three results are the same although the order is different. For example, the proposed framework produces first five results as: D5, D2, D7, D9, and D3 whereas first five results complied from the expert survey are: D7, D5, D2, D9, and D3.

The most difficult part in this exercise was to find and shortlist the most suitable people. They were approached and requested to spare some time for the survey. However, due to the busy schedule and tight deadlines, majority of the people missed the deadline. Upon reminders, we only succeeded to get less than 50% quality responses. Based on the results discussed in the following section, we conclude that the user rating on the post is near to the rating of the proposed framework. Table 7 shows the test of normality scores, while Table 8 represents the group statistics, and Table 9 depicts the independent sample test results. p-value of shapiro wilk test is < 0.05, so we reject Ho, concluding that the data is normally distributed.

TABLE 7. **Tests of normality.**

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Proposed Study	.312	10	.007	.775	10	.007
Expert Survey	.270	10	.037	.789	10	.011

a: Lilliefors Significance Correction

TABLE 8. **Group statistics.**

	Results	N	Mean	Std. Deviation	Std. Error Mean
Score	Proposed Study	10	6.7380	2.88807	.91329
	Expert Survey	10	4.5000	3.98999	1.26174

C. PERFORMANCE EVALUATION

For performance evaluation, we analyzed a data set from the Kaggle repository for human vital signs [37], which has vital signs sensor parameter readings. This data set includes vital signs parameters like monitoring time, body temperature, blood pressure, heart beat rate and oxygen saturation measures. Our objective was to predict the patient condition.

We applied the precision, recall, and F1 measure techniques on each user device This results in exploring the capabilities of the proposed solution in terms of how accurately it recognizes the most suitable used device. In this context, following formulae were used:

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{7}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \tag{8}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{9}$$

Equation (10), as shown at the bottom of the next page. Precision measures the accuracy of positive predictions made by a system. It tells us how well a model is performing. Whereas recall measures the proportion of actual positive instances that were correctly identified by the system. The computed scores of all three approaches are presented in Table 10. Figure 13 presents the results (computed through equations 7, 8, and 9). It is observed that the average precision value of the proposed framework (78.7) is better than the precision of the system proposed by Elhadj et al. [15] (77.44).

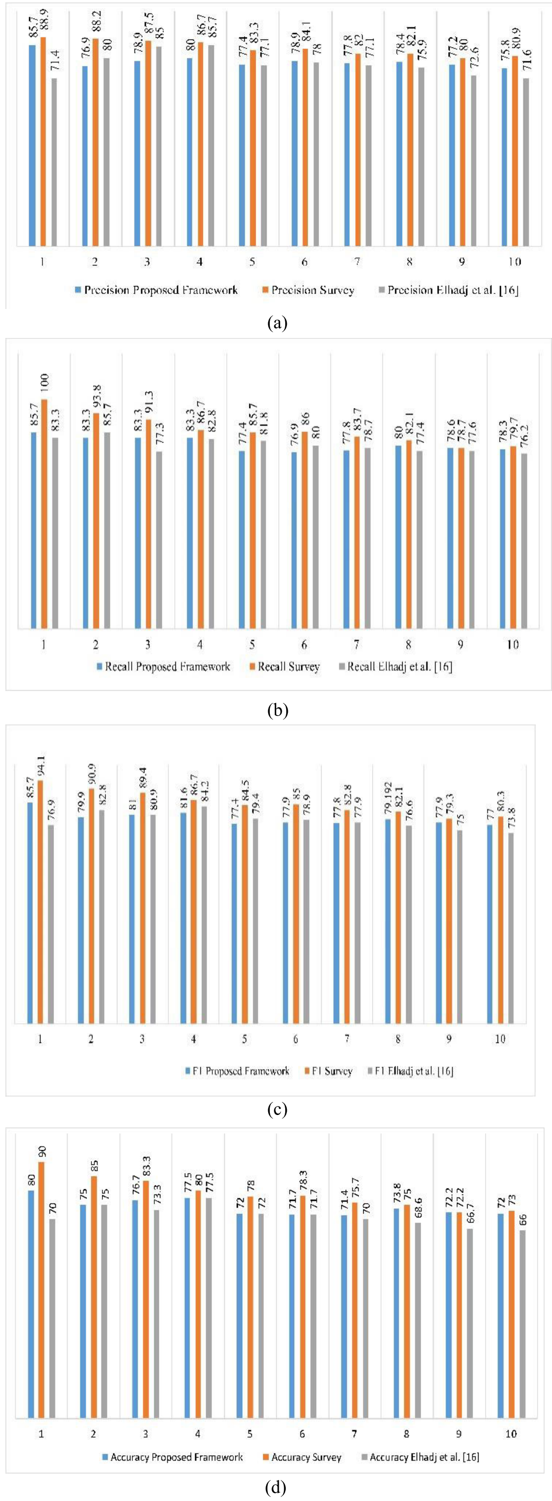

FIGURE 13. **(a). Precision scores of the proposed framework, survey and Elhadj et al. [15] approach. (b). Recall scores of the proposed framework, survey and Elhadj et al. [15] approach. (c). F1 scores of the proposed framework, survey and Elhadj et al. [15] approach. (d). Accuracy scores of the proposed framework, survey and Elhadj et al. [15] approach.**

TABLE 9. Independent sample test.

	Levene's Test for Equality of Variances		t-Test for Equality of Means					95% Conf. Interval of the Diff.	
	F	sig.	T	df	Sig. (2-Tailed)	Mean Diff.	Std. Error Diff.	Lower	Upper
Equal Variance Assumed	4.376	.051	1.437	18	.168	2.238	1.55759	-1.03438	5.51038
Equal Variance Not Assumed			1.437	16.4	.170	2.238	1.55759	-1.05742	5.53342

TABLE 10. Precision, Recall and F1 scores of proposed framework, expert survey and Elhadj et al. [15] approach.

% Patient Data	Precision			Recall			F1			Accuracy		
	Proposed Framework	Survey	Elhadj et al. [16]	Proposed Framework	Survey	Elhadj et al. [16]	Proposed Framework	Survey	Elhadj et al. [16]	Proposed Framework	Survey	Elhadj et al. [16]
10	85.7	88.9	71.4	85.7	100	83.3	85.7	94.1	76.9	80.0	90.0	70.0
20	76.9	88.2	80.0	83.3	93.8	85.7	79.9	90.9	82.8	75.0	85.0	75.0
30	78.9	87.5	85.0	83.3	91.3	77.3	81.0	89.4	80.9	76.7	83.3	73.3
40	80.0	86.7	85.7	83.3	86.7	82.8	81.6	86.7	84.2	77.5	80.0	77.5
50	77.4	83.3	77.1	77.4	85.7	81.8	77.4	84.5	79.4	72.0	78.0	72.0
60	78.9	84.1	78.0	76.9	86.0	80.0	77.9	85.0	78.9	71.7	78.3	71.7
70	77.8	82.0	77.1	77.8	83.7	78.7	77.8	82.8	77.9	71.4	75.7	70.0
80	78.4	82.1	75.9	80.0	82.1	77.4	79.192	82.1	76.6	73.8	75	68.6
90	77.2	80.0	72.6	78.6	78.7	77.6	77.9	79.3	75.0	72.2	72.2	66.7
100	75.8	80.9	71.6	78.3	79.7	76.2	77.0	80.3	73.8	72.0	73.0	66.0

Similarly, the average recall value of the proposed framework (80.46) is slightly better than the recall value of the system proposed by Elhadj et al. [15] (80.08).

Moreover, in patient care, providing accurate information timely is very significant. Incomplete or false data may cause wrong assessment that may result in worsen the problem. In this research, an ontological IoT framework for patient care has also been assessed for its accuracy (74.22%) which is 3 % better than the accuracy of the system proposed by Elhadj et al. [15].

Through analysis of results revealed that the consideration of context-awareness, quality of services, and the rich patient ontological concepts might be the reason for the improved results.

VII. CONCLUSION AND FUTURE WORK

Emergency services are important for every society to save lives of their citizens. These technology-based solutions are very complicated and complex due to the involvement of several factors like networks, artificial intelligence, knowledge engineering and system engineering etc. In this regard, internet-based technologies have played a major role to interconnect independent devices in an efficient and economical way. However, to deal with complexity (het erogeneity in terms of device data, languages and operating platforms etc.) and to develop dynamic, flexible, and cost-effective system, the semantic web can be used. Semantic web relies on ontologies which presents the data along with schema in an independent and machine processable format. To develop an ontology based IoT healthcare systems researchers have proposed several solutions with few shortcomings. For example, lack of agility, performance of devices and the accuracy of decisions. This research has proposed an ontology-based healthcare framework to organize the terms for describing the patients in a formal way. The framework consists of a knowledge base to keep record of

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + TrueNegative + FalsePositive + FalseNegative} \tag{10}$$

personalized information of patients, and support the medical staff in decision-making with the help of reasoning rules to detect inconsistencies in the available data. The main contributions of this work are as follows:

- Remote patient monitoring IoT ontology is proposed which considers the context-awareness along with the quality of services of IoT devices (Q1).
- Ontology-based reasoning rules are proposed for creating new knowledge. These rules can also be used to model implications for expressing the IoT domain data, mapping of different ontological concepts and translating device data (Q2).
- Ontology-based intelligent patient monitoring healthcare framework provides a set of guidelines to treat a patient. This framework is supported with algorithms for decision making (Q3).

In future, we intend to increase the precision of the proposed framework.

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