

Personalized, Ubiquitous Life-care Decision Support System (PULSE)

Technical Report

Version 2.0

Date: December; 2013

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Chapter 1: Introduction

1.1 Research Motivation

Technology has progressed at a fast pace in a decade and different industries are taking advantage from it for the betterment of common man. Healthcare domain is also progressing with the advancement of technology and is continuously evolving to adopt new technologies. PULSE-Chronic Disease is the system that is acknowledging the advancement of technology by incorporating the use of diverse information dataset for providing guidelines and recommendations to physicians and patients for improved life-care. It focus on personalized healthcare services provisioning by constructing intelligent knowledge-base using social interaction, sensory and clinical information. Security and healthcare cost are other motivating factors for this system and therefore we utilized cloud infrastructure to reduce healthcare cost and use anonymization techniques to support for security and privacy. Legacy systems easy integration with PULSE is another motivating factor to facilitate interoperability among heterogeneous systems for provisioning of recommendation services.

1.2 Introduction

Personalized Healthcare provides customized treatment and management plans for individuals for their better lifecare. Mainly it includes preventive, diagnostic, and therapeutic interventions to minimize the risk associated with patients. It also involves risk defined through genetics as well as clinical and family histories [Issa2009]. The main purpose is to involve patient in one's own wellness through self-directed care with improved patient's safety, quality and effectiveness of healthcare [Issa2009].

The spectrum for personalized healthcare includes many areas as shown in Figure 1.1. Health information technology played vital role in evolution of the healthcare domain. It also decreased the financial burden on patient and provided a way for the person to personal care as doctors are too busy to monitor them regularly. It also played its role in controlling the increased healthcare cost, so personal care will lead to patient staying healthier. Pervasive lifecare assistance shows the availability of healthcare to patient at anytime and anywhere. Medical data is increasing at a rapid pace and therefore health knowledge management is a key for personalized healthcare. Finally all these factors can be merged in a single aspect of providing decision support tools. These tools make sure that other factors discussed before are also made part of the personalized healthcare. We propose a decision support system that focuses on improving chronic disease

patient daily life activities by gathering data from different input sources.

Personalized, Ubiquitous, Lifecare Decision Support System (PULSE) for Chronic Disease system targets chronic disease patients by gathering data from multiple input sources including clinical, social media and sensory information. The data is obtained in standardized format and recommendations are generated for the patient. The recommendation is based on patient personal data collected from the different sources and therefore the recommendation is also personalized. PULSE-Chronic Disease system provides personalized services to patients in the form of recommendations divided into four categories: Patient Diagnosis, Food, Exercise and Medication services.



Figure 1.1 : Personalized Healthcare Spectrum

1.3 Problem Statement

Personalized healthcare envisions providing customized treatment and management plans to individuals at their doorstep. Key factors to ensure personalized healthcare is to involve with the individual in their daily life activities and process the gathered information to provide recommendations. We identified the mostly exposed domains for gathering chronic disease patient's information that includes: clinical, social media, and daily life activities. We propose a system called Personalized, Ubiquitous, Lifecare Decision Support System (PULSE) for chronic

disease to monitor the chronic disease patient gathered information from the sources mentioned above for providing recommendations. The prototype version developed for the system shows standardized system providing personalized services to chronic disease patients. This eventually results in improved lifecare and healthy living of the individuals.

1.4 Necessity of Research

1.4.1 Motivation of PULSE-Chronic Disease

PULSE-Chronic Disease is a decision support system that is based on healthcare standards use for provision of lifecare services to patients. It is based on self-evolutionary and dynamic knowledge base to store and process the data from different input sources such as clinical, social media and sensory data. It provides standard interfaces which allow integration with diverse applications, therefore existing healthcare systems can easily communicate with PULSE system and obtain recommendations. The proposed system also provides decoupled Knowledge Bases (KBs) to support heterogeneous KB Reasoner, such as standard based and non-standard based reasoners. Also, the system is based on individual ownership on KBs and the system is deployed on hybrid cloud. Security is key aspect of any decision support system and for ensuring personalized information exchange. Therefore, the system is also based on secured interfaces to share anonymized user's private data. Finally, comprehensive guidelines and recommendation for chronic disease patient is provided based on social, sensory and clinical datasets.

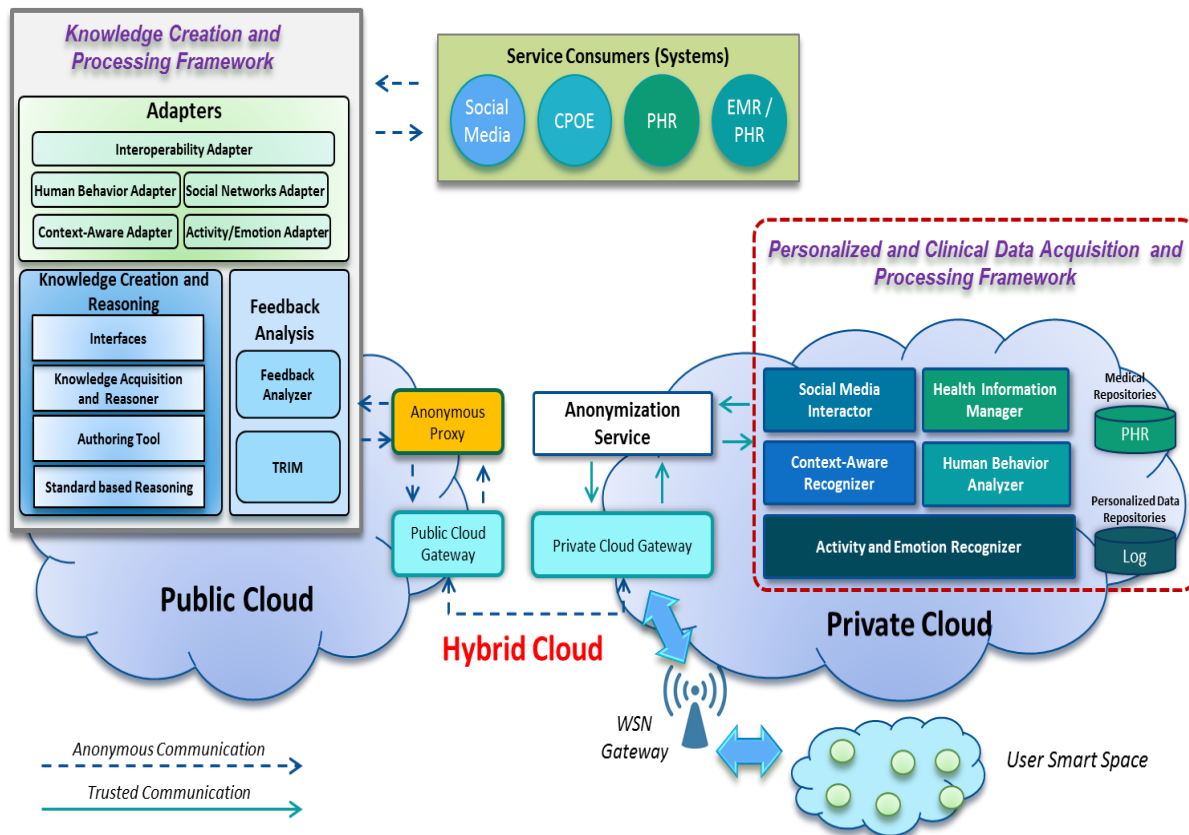
1.4.2 Uniqueness of PULSE-Chronic Disease

- Diverse data sources collection, aggregation and processing
- Dealing with diverse datasets such as clinical, social and sensory data for constructing intelligent personalized Knowledge-Base (KB)
- Standard based PULSE for chronic disease as a scalable solution
- Developing state-of-the-art, standard-based Healthcare Decision Support System that provides recommendations for chronic disease patients
- Facilitating interoperability among existing healthcare standards
- Evolutionary Knowledge Base populated by physicians and online resources
- Recommendations for chronic disease patients by absorbing heterogeneous data
- Standard and Mining based reasoning engine to process diverse data sources

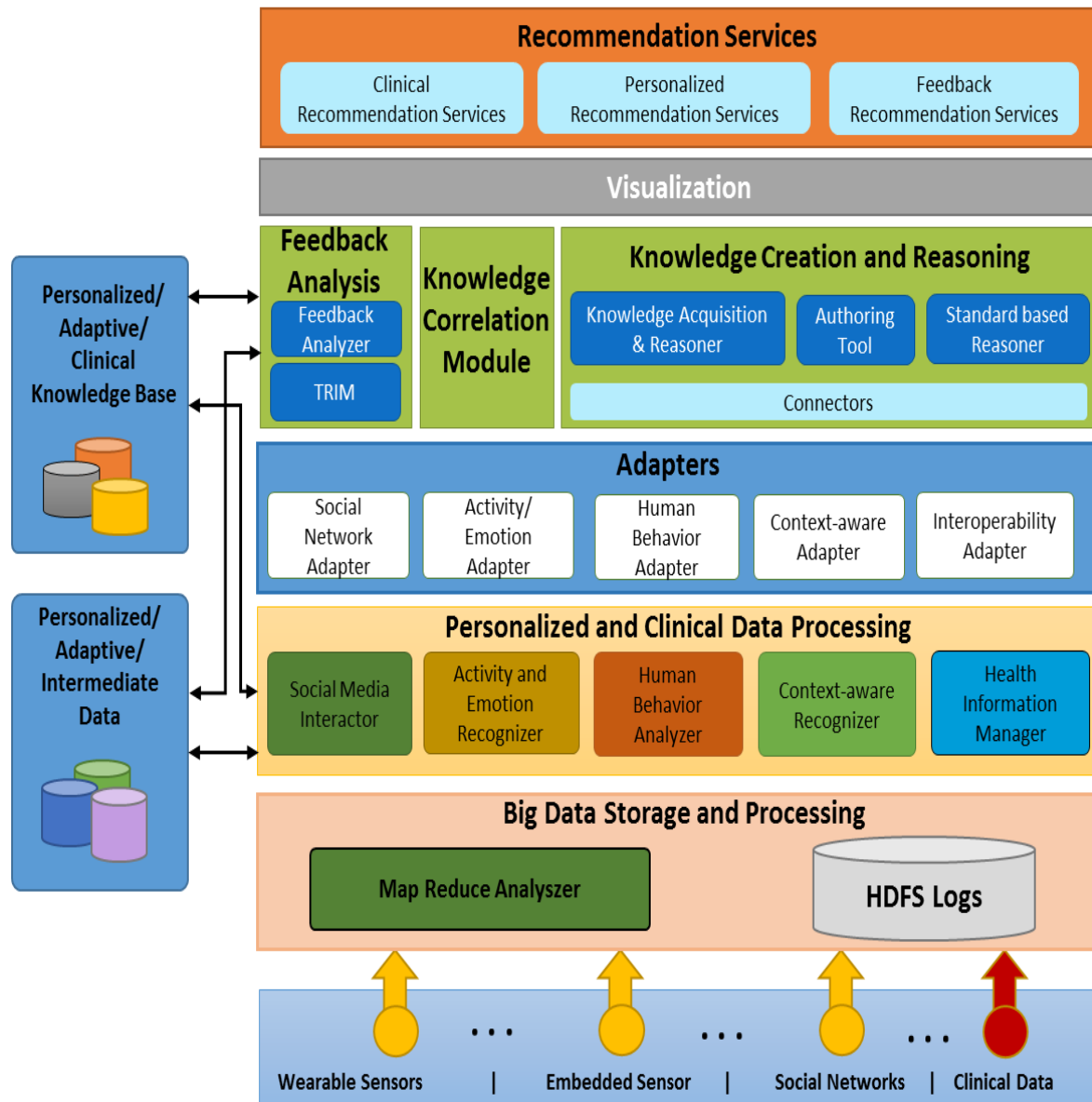
- Using technologies to provide personalized healthcare services based on activity, emotion recognition and context-awareness
- Utilizing cloud infrastructure for reducing healthcare cost and supporting security and privacy

1.5 Architecture

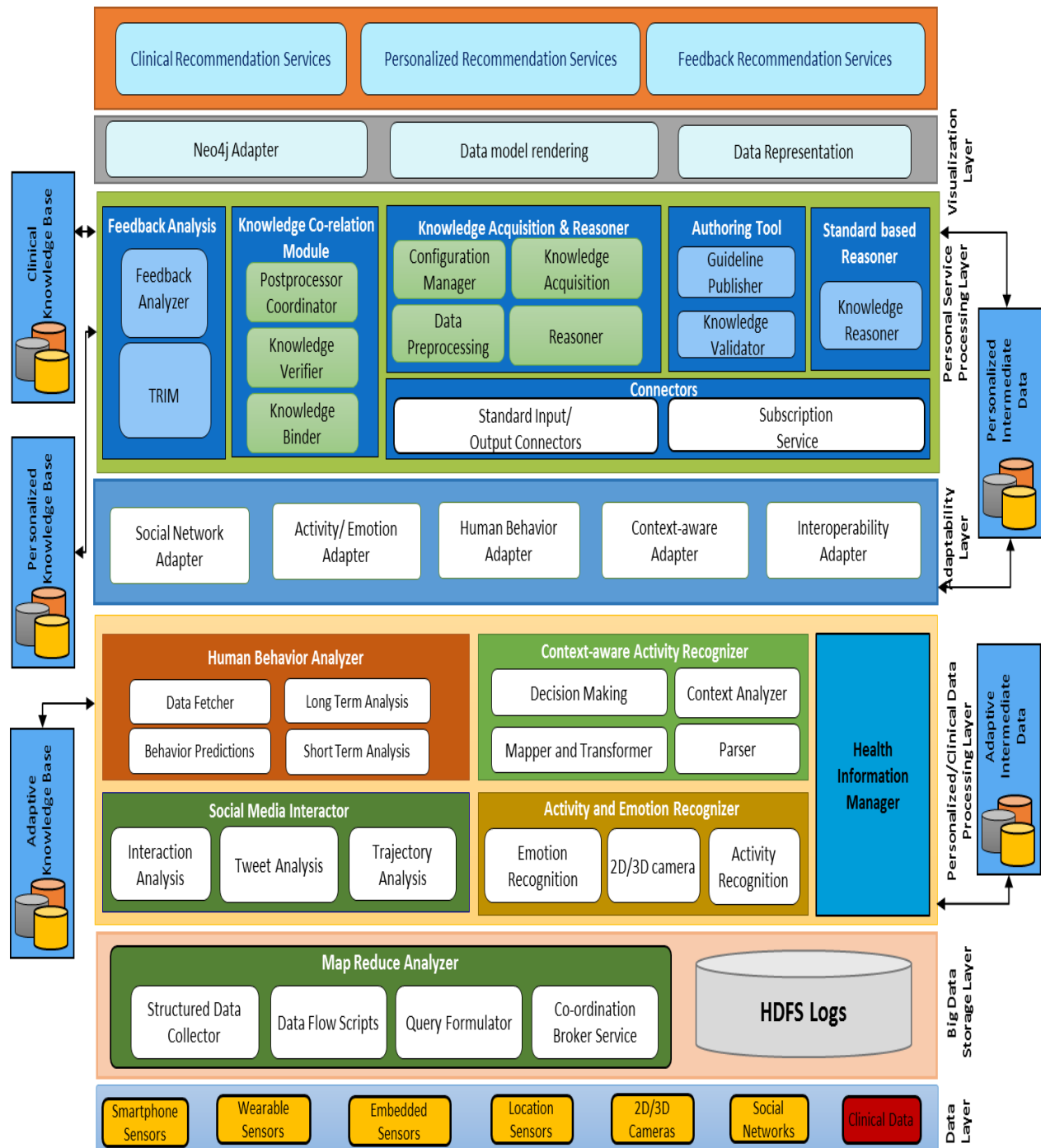
1.5.1 PULSE Architecture (Overview)



1.5.2 PULSE Architecture (Abstract View)



1.5.3 PULSE Architecture (Enterprise View)



Chapter 2: Personalized Information Processing

2.1 Adapter AER (Activity and Emotion Recognition)

- It consists of the multimodal sensor based activity and emotion recognition modules.
- The outputs of these individual independent modules are fuse together to predict the real-time high level contexts.
- The whole architecture is decomposed into the subcomponents and details are provided in the subsequent section.

2.1.1 Audio-based Emotion Recognition

2.1.1.1 Motivation

- Emotion is a mental state that arises spontaneously. In daily life, emotion is not only an effective way to convey our intention in communication but also a good indicator of our mental health. That is the reason why automatic detection of human emotions is an important factor to enhance the quality of the service provided by the computer such as human-computer interaction [Cowie2001, Schuller2004], lifestyle monitoring in ubiquitous health care systems [Tacconi2008].
- While human emotion can be expressed by a variety of physiological changes such as speech, blood pressure, heart rate, facial expression, etc.; many researchers prefer acoustic speech as a source of emotion [Ayadi2011, Bitouk2010, Iliev2010, Lee2005] because speech signal is the most commonly used and most natural method of human communication.
- Finding the best feature extraction and classification for emotion recognition from speech signal still are the current challenge for researchers.

2.1.1.2 Goals

- Propose a flexible engine that can be applied easily in different environment such as personal computer or smartphone and can work in real time environment.
- Process recorded audio signal from audio sensor to automatically recognize emotional states of user.
- Communicate with Fusion engine to collaborate with other sensors to provide accurately user's emotions by different means.

2.1.2 Video-based Activity Recognition

2.1.2.1 Motivation

- Automated systems are becoming increasingly involved in our daily lives. To correctly handle a situation either to help people to finish a job in a friendly environment or to prevent people from error in a hostile situation, the system must know what is happening. Human activity is a very important factor in this process. Knowledge of what people are doing can enable a wide range of assisting technologies, smart appliances, and aware environments.
- Human activity recognition has a good application in smart home technologies in all over the world to monitor human activities and take necessary steps. For instance, the SmartBo project in Norway includes a two-room house for the elderly with mobility impairments and cognitive disabilities. In this project, its main system including lighting, doors, windows, and shutters is controlled by smart devices and sensors and generates an alarm when something goes wrong [Elger1998].
- Security is another major application domain that requires an understanding of activity. Video surveillance is becoming standard in all sorts of public areas as well as the private backyard. Having a person behind each camera is simply impossible. An automated filter system as well as abnormal situation detection system has generated enough market demand for companies, which provides shopping customer identification.

2.1.2.2 Goals

- An active contour model is proposed that avoids the need of supervised learning using CV AC with Bhattacharya Distance.
- To make the model work smoothly with video data, we use optical flow the motion information.
- For feature extraction, wavelet transform is used, and the feature vector for each activity is obtained by taking the average of the whole frames frequencies.
- To recognize the human activities the Hidden Markov Model (HMM) is used.

2.1.3 Multimodal Sensor Fusion

2.1.3.1 Motivation

- Now-a-days, sensor technology is the more robust, cost-effective, less-intrusive and easy to install solution for recognizing the human activities [Turaga2008].
- Single sensor is not adequate to reflect the true context of humans, so multimodal sensors are required such as embedded sensors, wearable sensors and location sensors to recognize the true context.
- Fusion engine is an effective solution to combine the information from these heterogeneous modalities [Dante2010].

2.1.3.2 Goals

- To overcome the limitations of the existing systems and provide healthcare and smart homes services, there are different requirements that need to be satisfied.
 - Information coming from diverse sources intelligently fuse together like motion sensor, accelerometer, audio/video sensor, and location sensor.
 - To deal with different sources some synchronization process is required.
 - For the understandable output some auto-generated rules mechanism is to be needed to fulfill the requirements.

2.1.4 Video-based Emotion Recognition

2.1.4.1 Motivation

- Emotions are a universal means of communication which can be expressed non-verbally without any language constraints. They are recognized through facial expressions, voice tones, speech and physiological signals. Communication through facial expressions plays a significant role in social interactions. Over the last decade, automatic facial expressions recognition (AFER) has become an important research area for many applications such as child development, neuroscience and psychology, access control and surveillance and human behavior understanding.
- Anytime and anywhere, people have the ability to sense and express emotion, which can help make decisions, handle crises, and maintain relationships. Plentiful words and phrases are used to express moods and feelings. The ability of sensing and expressing emotion in a machine is often a luxury, considered unnecessary and functionless in basic computer intelligence. Programmers hardly encode emotion descriptions into computers. Why are people still trying to give computer emotional ability? [Malika2009].

2.1.4.2 Goals

- To propose a preprocessing technique in order to diminish the environmental effects such as lighting effects.
- To develop a robust face detection algorithm.
- To propose a new feature extraction technique that extract most informative from video frames for best accuracy of classification.
- Facial features are highly merged in the feature space, so to propose a non-linear classifier in order to discriminant different facial classes.
- To apply hierarchical recognition scheme in order to achieve high recognition rate.

2.2 Adapter CAME (Context Aware Manipulation Engine)

2.2.1 Motivation

As the human lifespan increases, people are becoming more interested in living a healthy life, which results in high-cost healthcare systems and services. Maintaining good quality and widely available healthcare services at a minimal cost is challenging [Khattak2010]. Home healthcare systems are becoming a more important form of healthcare service delivery. The management, maintenance, and coordination of healthcare services, educating users, and empowerment of individuals to manage their own health are the main focus. To support this, a powerful, flexible, and cost-effective infrastructure is required for healthcare services that can fulfill the vision of ubiquitous healthcare (u-healthcare). Cloud Computing can potentially provide a huge cost savings, flexibility, high-throughput, and ease of use for different services [Buyya2009] as well as for healthcare services. For this reason, we have developed an architecture, called Secured Wireless Sensor Network (WSN)-integrated Cloud Computing for u-LifeCare (SC3) [Hung2010]. Different wireless sensors are deployed that collect real-time data that is transmitted to a Cloud Server through a Cloud Gateway. Based on this real-time data collected by different sensors, SC3 provides real-time home care and safety monitoring services, an information sharing and exchange facility, emergency connection services, and patient monitoring and care services.

One of the main components of SC3 is the Human Activity Recognition Engine (HARE) [Khattak2010]. This engine is necessary to provide improved daily medical care and real-time reaction to medical emergencies, and identifying patient activities (i.e., Activity Recognition (AR))

is a prerequisite. Low level activities are defined as simple motions or actions detected by the sensing device that are very general and unclear in meaning such as hand movement. High level activities are the linkage of low level activities in a sequence with reference to context to make it more understandable. For example, in the process of making tea, picking up the cup, boiling water, using sugar, and using a spoon are all low level activities and are unclear when interpreted separately. However, when these activities are sequenced together and are used in context with the kitchen location, then they comprise “making tea” as a high level activity.

Our focus is on CAME [6] as a component of our proposed HARE [Khattak2010] that is beyond the limits of traditional systems. We propose the integration of all the activities detected using different types of sensors together along with context and profile information of the subject. We model the activities in domain ontology within the explicit context of the activity and execution pattern. In addition, we apply semantic reasoning to infer high level activities (user intention for performed activity) and use it for decision making. This will help in enhancing capabilities of healthcare systems to facilitate more personalized recommendations and decision making, and it has tremendous value for intelligent/efficient service provisioning.

For the CAME implementation, we use different sources of information to avoid the possibility of missing information or imperfect context information [Henricksen2004]. For context representation and profile information, we use an ontology and have developed a semantic structure for information representation. Ontology is formally defined as an explicit and formal specification of a shared conceptualization [Gruber1993].

Sensors are deployed to collect real-time data about a person’s activities and environmental information. Then with the use of an ontology (containing expert knowledge of the medical domain and user profile information) these detected activities are intelligently manipulated to infer higher level activities and also to make a situational analysis. The experimental results of the match-making process of CAME yielded good results. Rule-based filtering for situation analysis and decision making has verified our claims, and the results of activity recognition and manipulation are very encouraging in terms of accuracy. CAME uses both A-Box (instance level) and T-Box (structure level) inference techniques that confer better accuracy. A filter is also implemented in CAME to filter out an “unknown activity” during the match making phase. This not only improves the accuracy of the CAME, but also results in better system response time.

2.3 Adapter Social Media Interaction Engine

2.3.1 Motivation

Chronic disease accounts for more than 75% of healthcare expenditure and nearly an equivalent percentage of disease-related deaths [Alwan2011]. Its disorders are generally characterized by long duration and slow progression. With enough care and supervision, health condition of these patients can be improved. CDSS (Clinical Decision Support System), based on health information systems, (e.g., EHRs, EMRs, PHRs, and CPOEs) assist physicians in the clinical processes of patient's care [Soumeiya2012]. Our lab developed CDSS called Smart CDSS that caters the different aspects of patient's lifestyle in addition to clinical information [Hussain2012]. Smart CDSS links health observations with contextual knowledge to influence the decisions of clinicians for improved healthcare. The most common applications of a Smart CDSS include alerts and reminders, diagnostic assistance, and prescription support [Soumeiya2012] [Hussain2012].

In the field of healthcare, recently researchers have realized the importance of social media as a potential domain for real time healthcare provisioning [H.R.Institute2012]. Social media empowers users to know more about themselves including their health conditions. For example, research [S. Fox2012] investigated that four out of five users are using internet to find out personalized healthcare information related to the particular disease and its treatments. By knowing more about health, people will be more prepared to manage minefield of modern medical treatment. The challenge lies here is that how social media can be effectively utilized to manage health related issues

2.3.2 Goals

In this research, our aim is to improve the patients' health and lifestyle by utilizing his/her social interaction based on different social networks. For instance, after observing a patient's daily social media activities, our proposed SMIE (Social Media Interaction Engine) finds some complications with his/her lifestyle like he/she usually sleeps late; does not exercise regularly; does not take medicine on time; eats too much. Obviously, these lifestyles are not good for chronic disease patients [Fatima2010]. The proposed SMIE is integrated through social media adapter in the Smart CDSS. The social media adaptor is a bridge to connect the SMIE with Smart CDSS. The extracted knowledge from SMIE is converted into standard vMR (virtual Medical Record) [Huang2006]

format to facilitate the Smart CDSS decision making and recommend changes in unhealthy lifestyles in better way.

The proposed system monitors health conditions, emotions and interests of patients from patients' tweets, trajectory and email interaction. We extract keywords, concepts and sentiments from patient's tweets data. Trajectory analysis identifies the focused activities after considering imperative location and semantic tags. Email analysis finds interesting patterns and communication trends from daily routine of patient. Therefore, learning about patients' lifestyles becomes an important step towards allowing Smart CDSS to provide personalized services more accurately and effectively. However, to the best of our knowledge, there is not any existing system available which utilizes these social networks with their potential role in decision making for healthcare. Our result shows a proof of concept that has been implemented to reflect the complete working flow of SMIE.

2.4 Big Data Service Engine

2.4.1 Motivation

Advancement of digital sensors in daily life devices as well as wearable devices have resulted in huge amount of data. The data gathered is of different varieties and it is getting harder for conventional DBMS. So big data technologies is a very viable solution to this situation. The big data technologies are used for unstructured data which is too much to handle for the relational databases in terms of size, the velocity of data and different varieties of data. The big data service engine will gather all the data in the sensor layer and structure it for DBMS so that it can be real time.

2.4.2 Goals

- Structure the data for real time access
- Store the data in a distributed and fault tolerant manner
- Get a big data solution for ATHENA for future references
- Generate a sql interface for data extraction
- Generate a sql script of insert queries for data population

2.5 Knowledge Acquisition and Reasoning Engine

2.5.1 Motivation

Manual creation of knowledge with ever growing personalized data is not a feasible task in terms of labor, cost, and time. To overcome this situation, automatic knowledge acquisition techniques are needed for the generation of knowledge from the personalized data sources. At the same time, personalized healthcare services are needed to be provided to the users at run time so that to improve their health quality. For these reasons, an automatic reasoning engine is needed to answer the users query and generate recommendations.

2.5.2 Goals

The knowledge acquisition and reasoning engine (KARE) is aimed to provide personalized wellbeing services for u-lifecare. The goals to be achieved are listed below:

- To prepare multimodal personalized data in the form of a unified dataset
- To automatically acquire knowledge from vast amount of data by using different machine learning approaches
- To develop an integrated system both for knowledge acquisition and inference in one package
- To develop hybrid reasoning architecture for Life care applications.
- To generate personalized recommendations for wellbeing of human being.

Chapter 3: Adapter Interoperability ENgine (ARIEN)

3.1 Motivation

PULSE-Chronic Disease takes clinical data from HMIS for processing using Adapter Interoperability Engine (ARIEN) component. Heterogeneities among HMIS compliant standard and PULSE-Chronic Disease compatible standard exists. ARIEN resolves these heterogeneities for HMIS's to interact easily with PULSE-Chronic Disease to utilize its services. It behaves as mediator between the two systems. HMISs compliant to different healthcare standards understand only the standardized format such as: HL7 CDA, openEHR, CEN 13606, while PULSE-Chronic Disease can only process virtual Medical Record (vMR) format. ARIEN provides bridge services that use ontology matching techniques to generate mappings between heterogeneous healthcare standards for automatic transformation of information to enable interoperable communication among healthcare systems.

3.2 Goals

- Processing clinical data to build up clinical knowledge base
- Providing interoperability among medical systems and DSS
- Mapping service for conversion between medical systems compliant standards and DSS compliant standard
- Accuracy and continuity of mappings between healthcare standards with vMR
- Integrating legacy EMR/EHR/PHR/CPOE systems with DSS

3.3 Related Work

For achieving interoperability in healthcare domain, some systems have used ontology matching, SOA architecture, and also semantic web services framework. Some of these systems, closely align with the proposed system are discussed below;

Jini Health Interoperability Framework (HIF-J) [ducrou2009] uses Jini technology which is based on SOA. The main purpose of HIF-J is to exchange semantically interoperable messages. It provides translation services, that behaves as a mediator between standards. These translation services convert message instances HL7 V2 and V3 and also HL7 and openEHR message instances. It is based on XSLT transformations between message instances of different standards.

Since standards are growing with new domains, so managing XSLT becomes very difficult. Moreover, XSLT is just transforming syntactic structure and semantic transformation is not achieved.

Artemis [dogac2006] project is based on achieving semantic interoperability between healthcare systems by using semantic web services. It also uses the concept of semantic mediation which focuses on resolving the heterogeneities between different standards. It mainly focuses on resolving the heterogeneities between HL7 V2 and V3 standards. Artemis uses OWLmt tool which is an ontology mapping providing a graphical user interface to define the mappings between two ontology schemas. It is limited only to conversion between HL7 V2 and V3 standards.

PPEPR [sahay2008] project is an integration platform that focuses on resolving the heterogeneity problem between two version of the same standard HL7 (V2 and V3). It is based on semantic SOA concepts and solves the problem of interoperability at the semantic level. It used Web Service Modeling Ontology (WSMO) approach unlike Artemis which uses OWL-S. It mainly focuses on integration of Electronic Patient Records and conversion between HL7 V2 and V3 is specified. The scope is only limited to transformations between standards that's comes under the umbrella of HL7.

Ortho-EPR [magni2007] standard is a proposed standard that is based on the integration of HL7 and DICOM standards for electronic orthodontic patient records. The main purpose of this standard is storage and communication of orthodontic patient records. The message part is handled by HL7 while imaging is handled by DICOM and there integration results in Ortho-EPR standard. Its main purpose is the integration of two standards and not interoperability between standards.

In [Khan2009], the authors focus on semantic process interoperability with the help of interaction ontology in HL7 V3. Interaction ontology is responsible for handling the heterogeneities between processes of different healthcare organizations compliant to HL7 V3 standard. This work is only related to semantic process interoperability using standard HL7 V3 and semantic data interoperability is not discussed.

Existing systems mainly focuses on the conversion of instances between different standards while our focus is on the accuracy of mappings in addition to conversion of instances.

3.4 Architecture

- **Accuracy Mapping Engine**

This component deals with the generation of ontology mappings. CDA and vMR ontologies developed are mapped using ontology matching techniques such as string based, child based, property based and label based matching techniques. These matching techniques are used by our matching system called *System for Parallel Heterogeneity Resolution (SPHeRe¹)*. SPHeRe takes as input the source and target ontologies for matching and the mappings generated are stored in *Mapping Repository* in the form of *Mediation Bridge Ontology (MBO)*. *MBO* behaves as a mapping file repository for storage of mappings. Another approach that we use for increasing the accuracy of mappings is *Personalized-Detailed Clinical Model (P-DCM)* [Khan2013] approach. P-DCM approach uses organizational conformance information to improve accuracy level of the mappings stored in the *MBO*. This covers the expert verification and manual mappings aspect of the ARIEN system as all the organizational information is stored in the P-DCM ontology. *P-DCM* and *Expert Verifications* improves the overall accuracy of the mapping file. Standards can evolve with the passage of time by accommodating new changes, therefore requiring continuity of mappings of *MBO*.

- **Standard Ontology Change Management**

Standard Ontology Change Management component is responsible for reflecting the changes in the mappings generated that are necessary after change occurs in any or both source and target ontologies. *Change Detector* always listens for any change in the mapping ontologies. The change information is accessed by *Change Collector* once that change is detected by *Change Detector*. This information is then provided to *Change Formulator* for converting the changes into processable format. Matching of only the changes with the target ontology is carried out and reflected in the already stored mappings in the form of updation.

- **Transformation Engine**

Transformation Engine component performs the conversion of standard formats by communicating with the HMIS. *Communication Content Handler* access information from the HMIS in HL7 CDA format and forwards it to *Conversion Engine*. *Conversion Engine* uses mappings from *MBO* to convert from HL7 CDA standard format to vMR

¹ <http://uclab.khu.ac.kr/sphere>

format for Smart CDSS to process and generate guidelines. In the same way when the guideline are to be provided to HMIS, conversion from vMR to CDA format is performed.

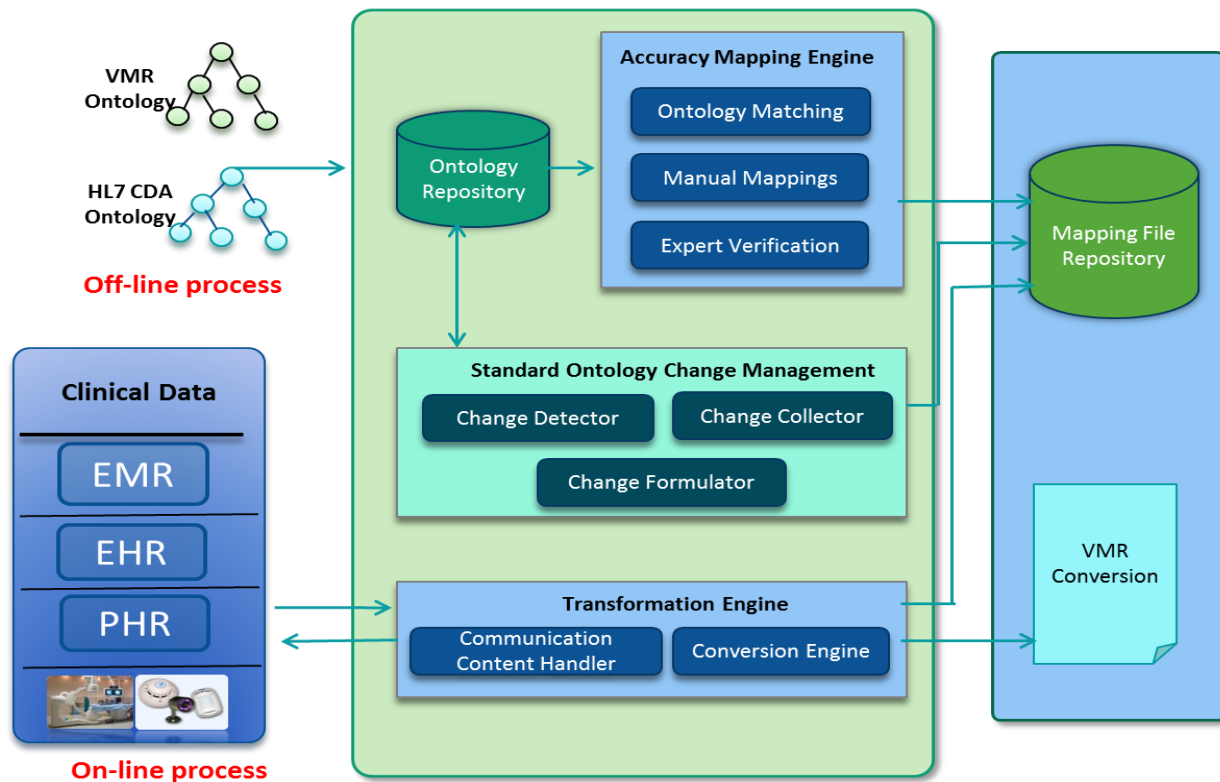
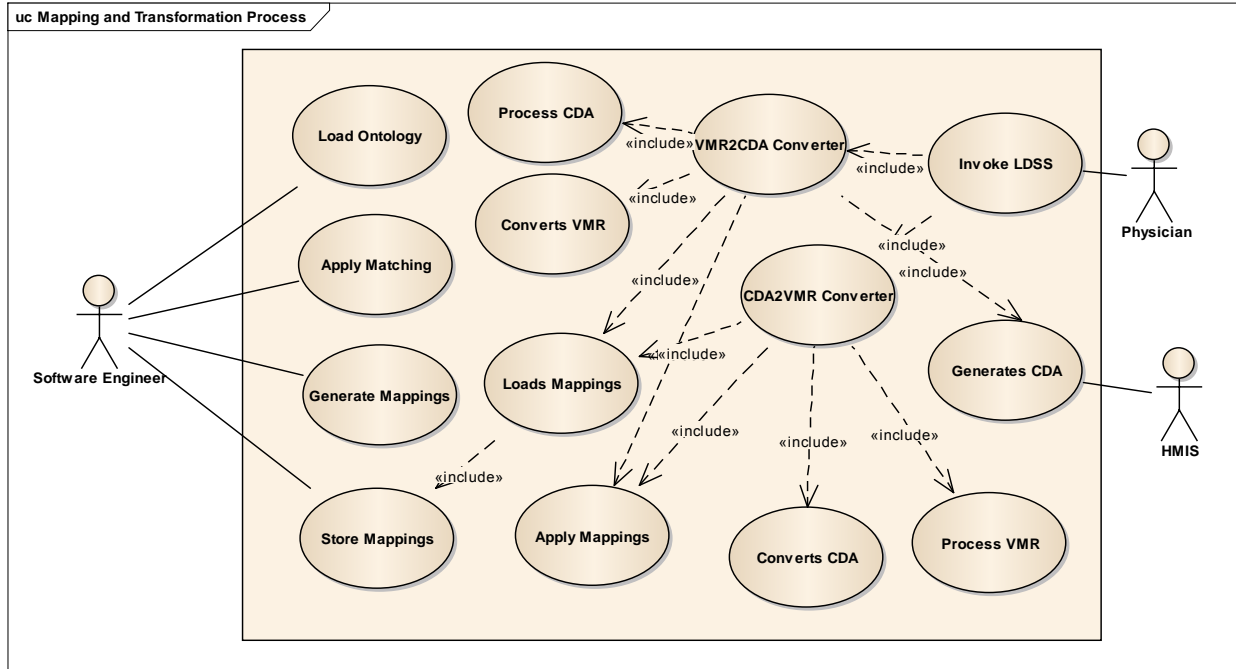


Figure 3.1: ARIEN Architecture

3.5 Uniqueness

- Interoperability Adapter uses mapping service for conversion of clinical data into DSS standard format and vice versa
- Mapping Service is based on storage of mappings in Bridge Ontology (a mappings storage representation ontology)
- Accuracy of mappings is maintained for less data loss while conversion

- Changes in medical ontologies is catered by ensuring continuity of mappings



3.6 UML Diagrams

3.6.1 User Classes and Characteristics

- Actors

1. Software Engineer

Software Engineer is responsible for generating the ontology mappings using different ontologies and storing the generated mappings in a repository.

2. Physician

Physician interacts with the system by entering the required data that is converted to HMIS compliant standard format.

3. HMIS

HMIS is responsible for converting the physician entered information to standard format.

3.6.2 Use Case Model for Mappings Generation and Transformation

Use Case Description

- Load Ontology

Load Ontology use case loads the ontologies on which ontology matching needs to be performed. It loads the source and target ontologies for matching purpose.

- **Apply Matching**

Applies Matching is the use case that is responsible for selecting the matching techniques that needs to applied for ontology matching process. It applies the ontology matching techniques to generate mappings.

- **Generate Mappings**

Generate Mappings use case applies ontology matching process and generates the mappings between source and target ontologies.

- **Store Mappings**

The mappings generated are then stored in repository by Store Mappings use case. The repository contains many mapping files.

- **Invokes LDSS**

Invokes LDSS use case is responsible for connecting the HMIS with the PULSE. It includes converters for different standards.

- **Generates CDA**

Generates CDA use case is used for creation of CDA instance from the data entered by the physician.

- **VMR2CDA Converter**

VMR2CDA Converter use case coverts PULSE standard format that is VMR to HMIS standard format which is CDA.

- **CDA2VMR Converter**

CDA2VMR Converter use case coverts HMIS standard format which is CDA to PULSE standard format that is VMR.

- **Process CDA**

Process CDA use case processes CDA instance information and its constructs are accessed for applying the mappings stored in the repository.

- **Converts VMR**

Converts VMR use case performs conversion from CDA format to VMR format using specific mappings generated from VMR and CDA models.

- **Process VMR**

Process VMR use case processes VMR instance information and its constructs are accessed for applying the mappings stored in the repository.

- **Converts CDA**

Converts CDA use case performs conversion from VMR format to CDA format using specific mappings generated from VMR and CDA models.

- **Load Mappings**

Load Mappings use case access the mapping repository and loads the required mappings to be used for conversion purpose.

- **Apply Mappings**

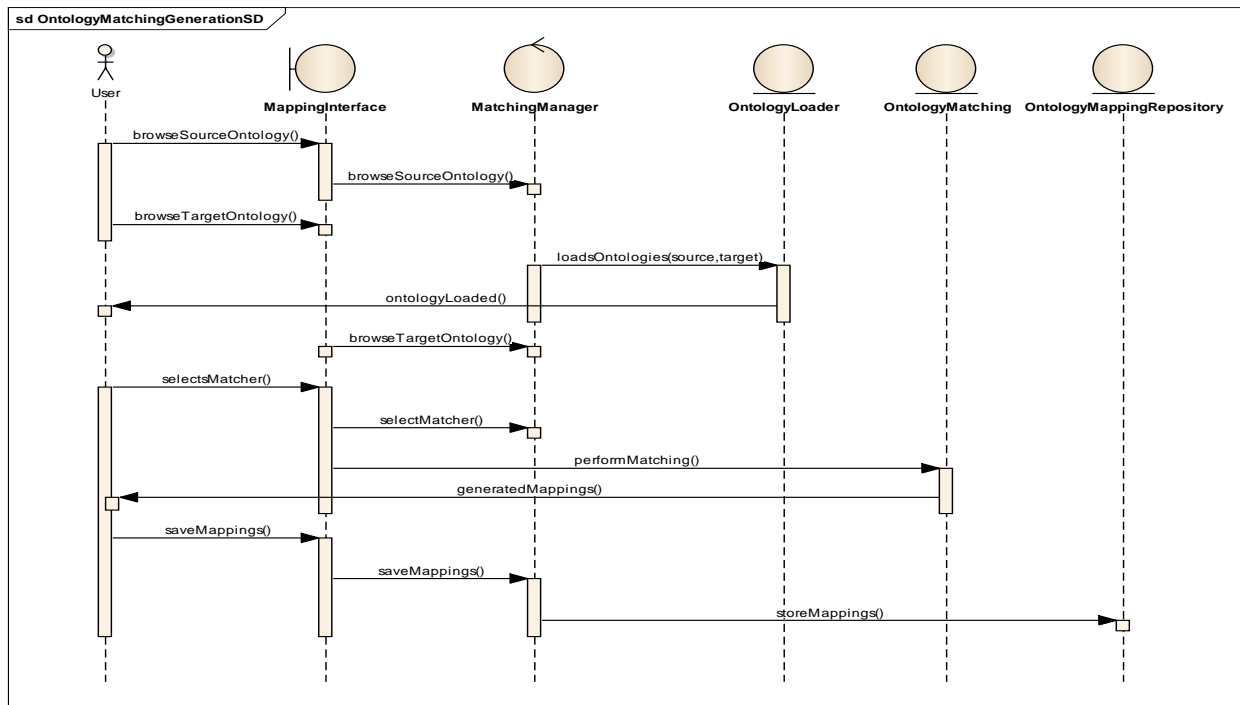
Apply Mappings use case applied the loaded mappings for conversion from one standard format to another standard format.

3.6.3 Interaction Model

Sequence diagrams are described as follows that shows the interaction between different objects.

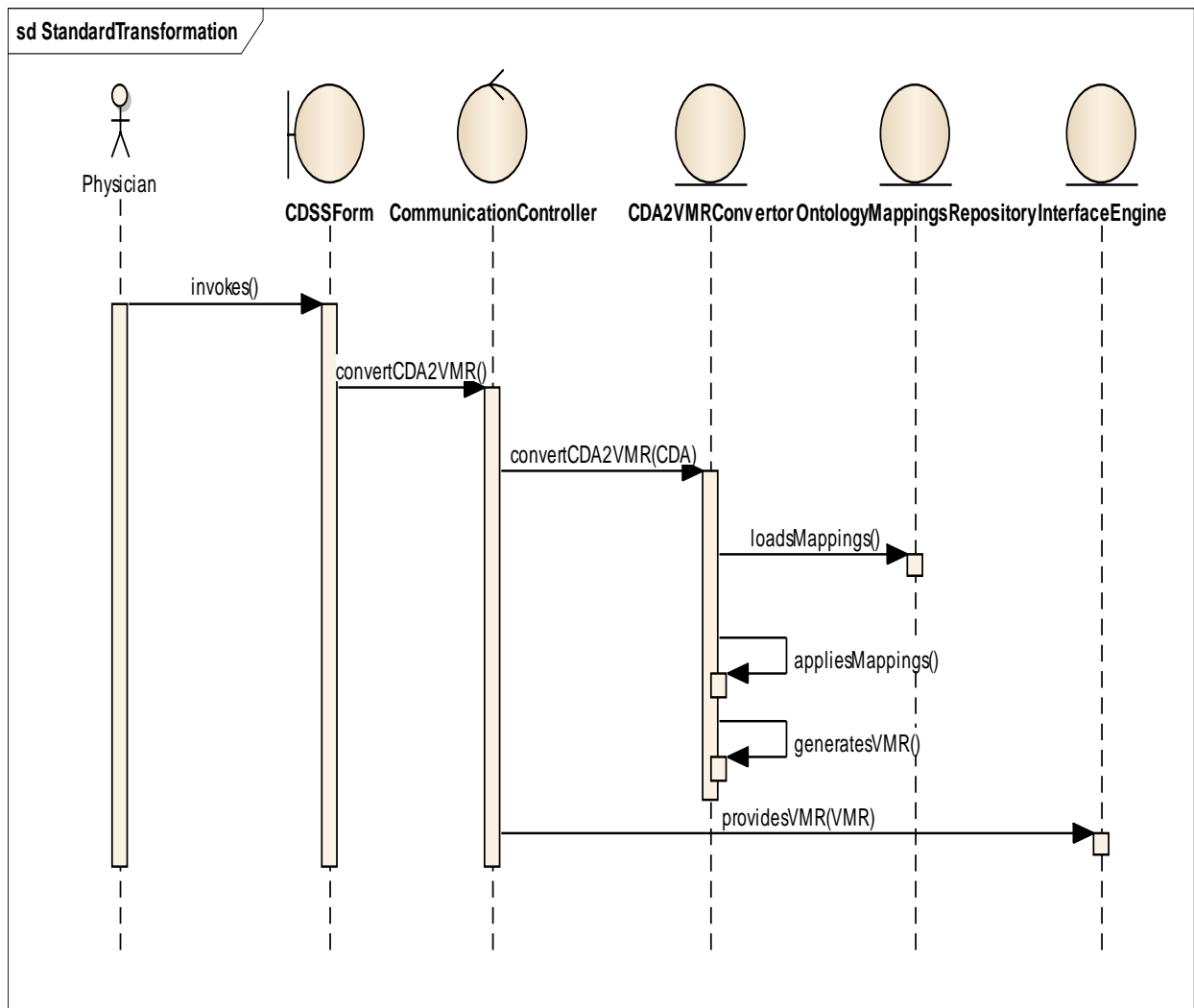
- **Generate Ontology Mappings**

User browses the source and target ontologies using loadOntologies(source,target) method. The ontologies are loaded by ontologyLoader() method by OntologyLoader object. User selects the matcher using selectMatcher() method for the performMatching() method to be performed by OntologyMatching object. Finally the user store the mappings using saveMappings() method.



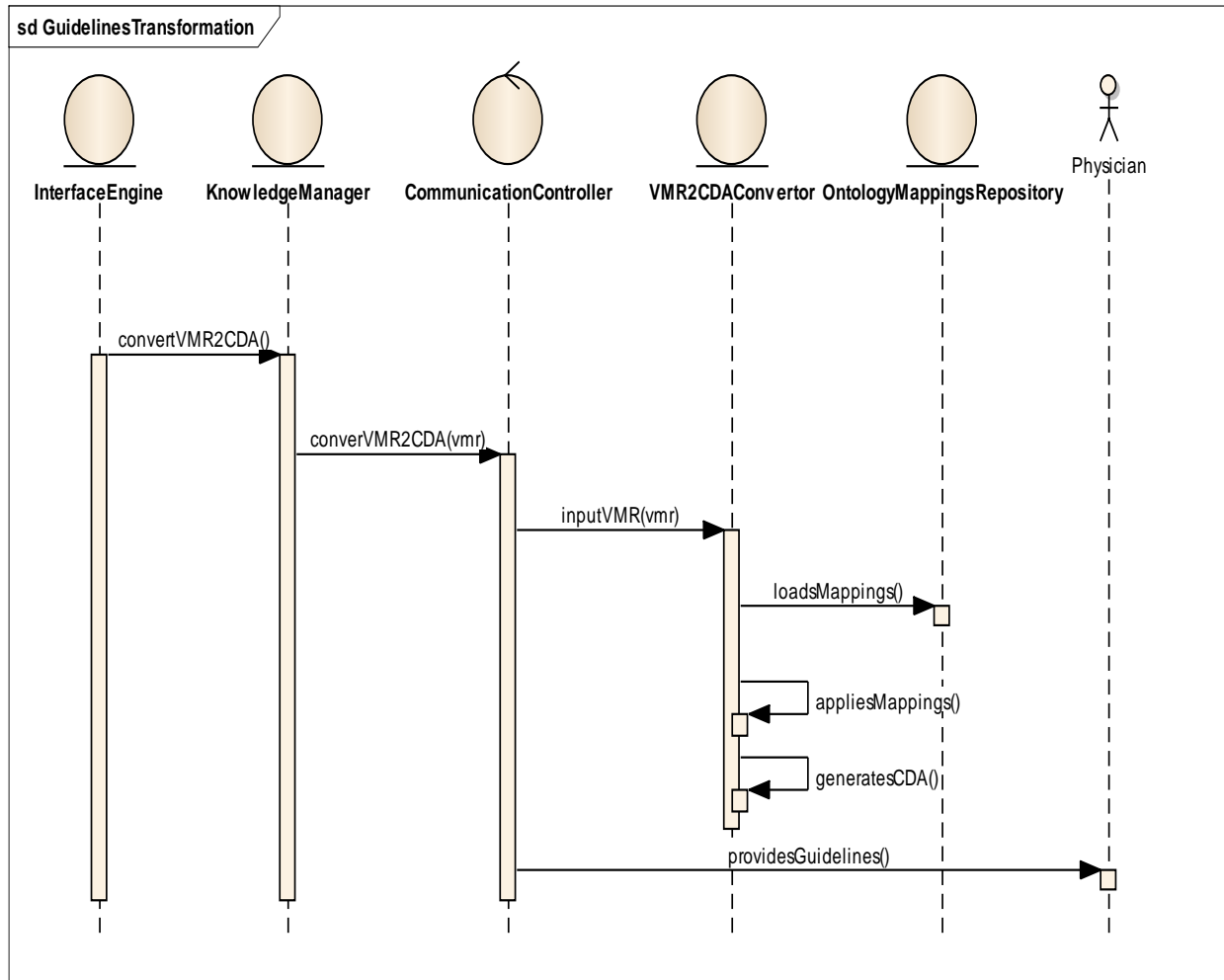
- **Transform Standard Format**

Physician invokes the PULSE and provides information in CDA format. CommunicationController object access the CDA format and calls convertCDA2VMR() method. The mappings are loaded using loadMappings() method by the CDA2VMRConverter object to apply mappings and generate the corresponding VMR using generateVMR() mappings. Finally the generated VMR is accessed by the InterfaceEngine object for final concatenated VMR creation. The concatenation process is responsibility of the Fusion Adapter module.



- **Transform Guidelines**

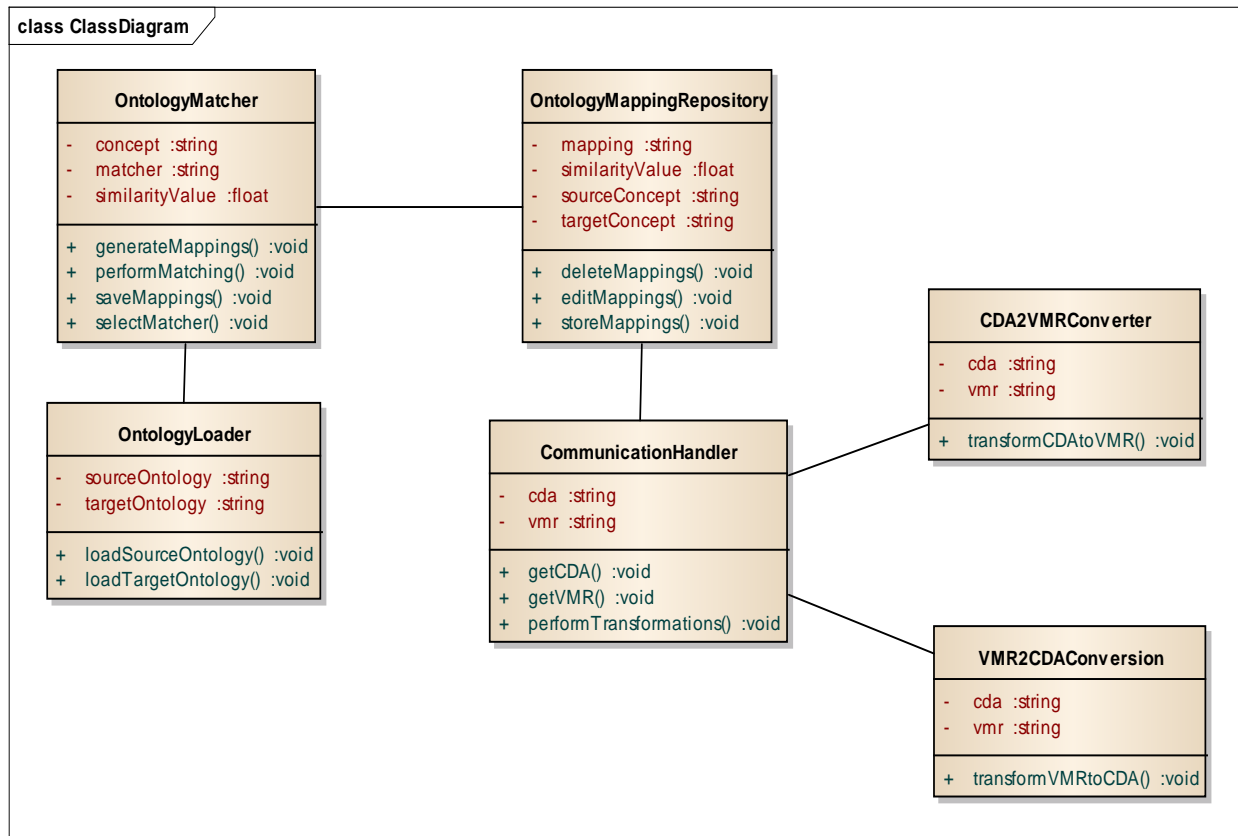
The Knowledge Manager module generates the guidelines and provides to the InterfaceEngine in VMR format. InterfaceEngine forwards the generated guidelines in VMR format to CommunicationHandler object that provides it as input to VMR2CDAConverter object. VMR2CDAConverter object loads the mappings using loadMappings() method and further uses appliesMappings() and generatedCDA() functions to convert the VMR format to CDA format. Finally the generated CDA is provided to HMIS compliant to CDA that shows the guidelines to physician in a user friendly manner.



3.6.4 Class Diagram

Class diagram shows the different classes and their relationships with each other. The class diagram for ARIEN system shows classes and their dependencies with each other. Initially the OntologyLoader class loads the source and target ontologies. These ontologies are used for mappings generation among different standards and therefore are passed to OntologyMatcher class. OntologyMatcher class performs ontology matching techniques to generate mappings. These generated mappings are passed to OntologyMappingRepository class for storage purposes. The mappings are stored by OntologyMappingRepository class and it can edit the mapping by performing delete, store and edit functions. These mappings are then used for transformation of one standard to another. CommunicationHandler class access the CDA format from HMIS and

provides this information to CDA2VMRConverter class. CDA2VMRConverter class is responsible for using the mappings stored to convert CDA format to VMR. In the same way VMR2CDAConverter performs the opposite function by converting VMR format to CDA format.



3.6.5 Detailed Description of Components

The component diagram of ARIEN shows the different components and their relationships with each other. Also it shows the subcomponents of the main components and their relationships with each other. Mainly three components are included in the ARIEN module. These are explained as follows:

- **AccuracyMappingEngine Component**

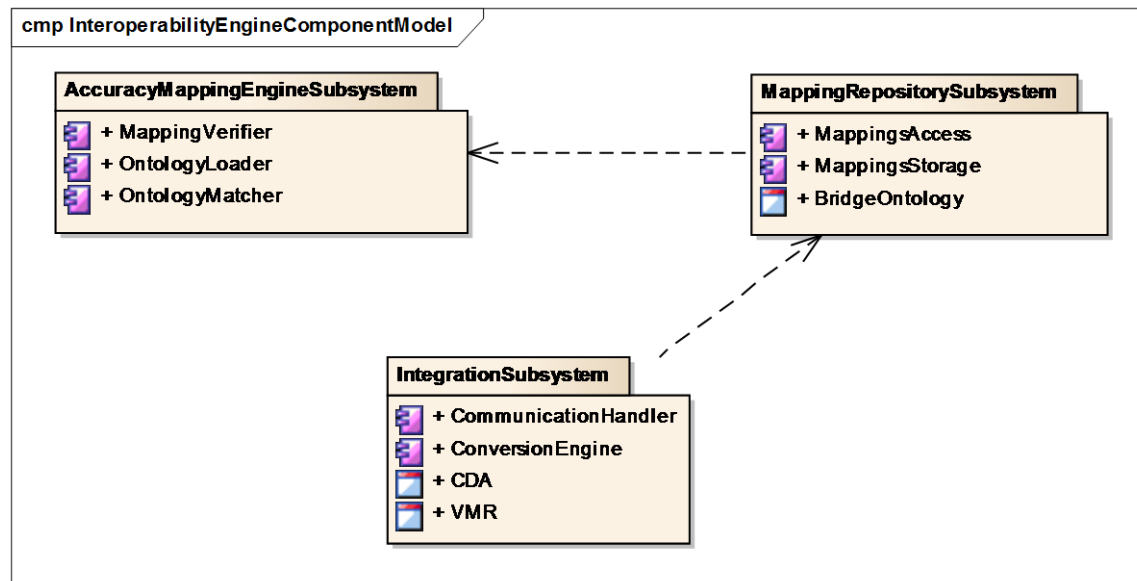
It is the main component of Adapter Interoperability Engine that is used for generating the mappings between different healthcare standards and then storing them. It is composed of subcomponents like **OntologyLoader**, **OntologyMatcher** and **MappingVerifier**.

- **MappingRepository Component**

Another main component is the MappingRepository that is used to store the mappings in the form of Bridge ontology. This component also consists of two subcomponents MappingAccess and MappingStorage.

- **IntegrationModule Component**

IntegrationModule is another main component that is used to use the mappings generated by AccuracyMappingEngine and stored in MappingRepository. These mappings are used for transformation purpose between different standard formats. It includes subcomponents like CommunicationHandler and ConversionEngine.



- **OntologyLoader Subcomponent**

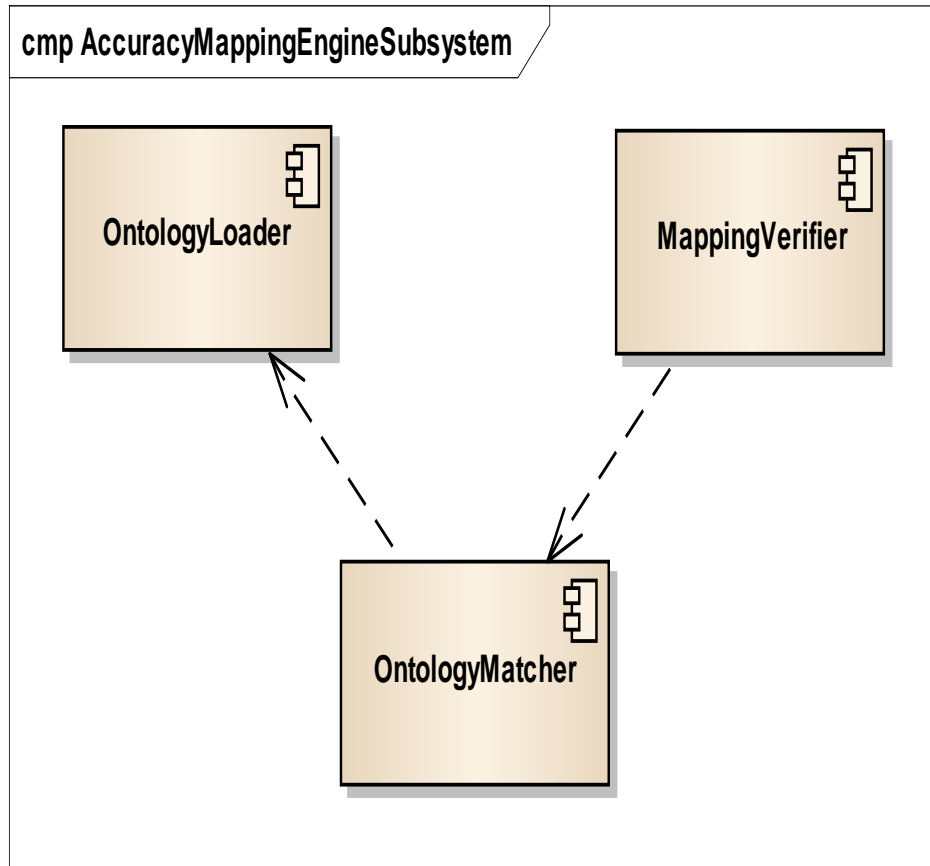
OntologyLoader is the subcomponent of AccuracyMappingEngine component and is used for loading the source and target ontologies for mappings generation.

- **OntologyMatcher Subcomponent**

OntologyMatcher is the subcomponent of AccuracyMappingEngine component and is used for generating the mappings between different standards using various ontology matching techniques.

- **MappingVerifier Subcomponent**

Mappings generated by OntologyMatcher subcomponents require verification that is carried out by the MappingVerifier subcomponent.



- **MappingStorage Subcomponent**

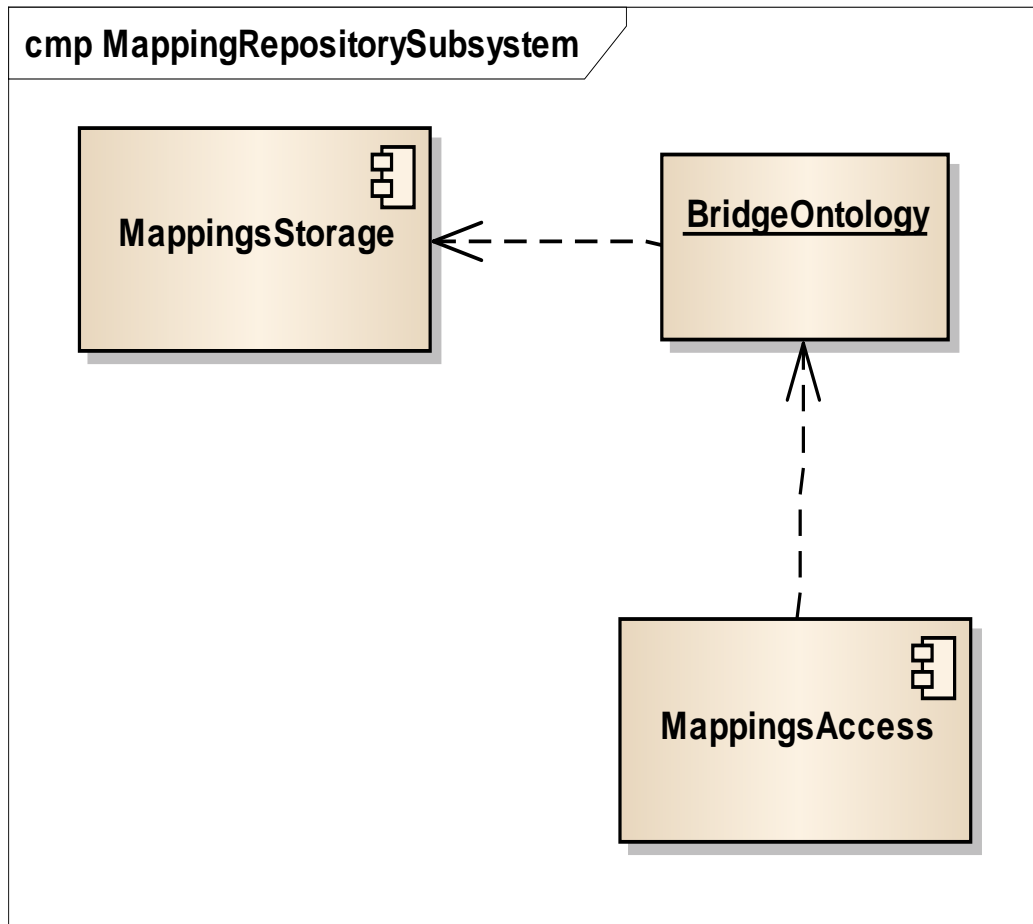
MappingStorage is the subcomponent of MappingRepository component and is used for storing the mappings generated using ontology matching techniques. This component gives the mapping file a structure and stores it in RDF format.

- **MappingsAccess Subcomponent**

MappingsAccess is the subcomponent of MappingRepository component and is used for providing the required mappings to the conversion engines for transformation from one standard format to another.

- **BridgeOntology Object**

BridgeOntology object is created by the MappingStorage subcomponent and is used by the MappingAccess subcomponent for transformation purpose.



- **CommunicationHandler Subcomponent**

CommunicationHandler is the subcomponent of IntegrationModule component and its primary purpose is to obtain HMIS compliant standard format and provides it to ConversionEngine for applying mappings.

- **ConversionEngine Subcomponent**

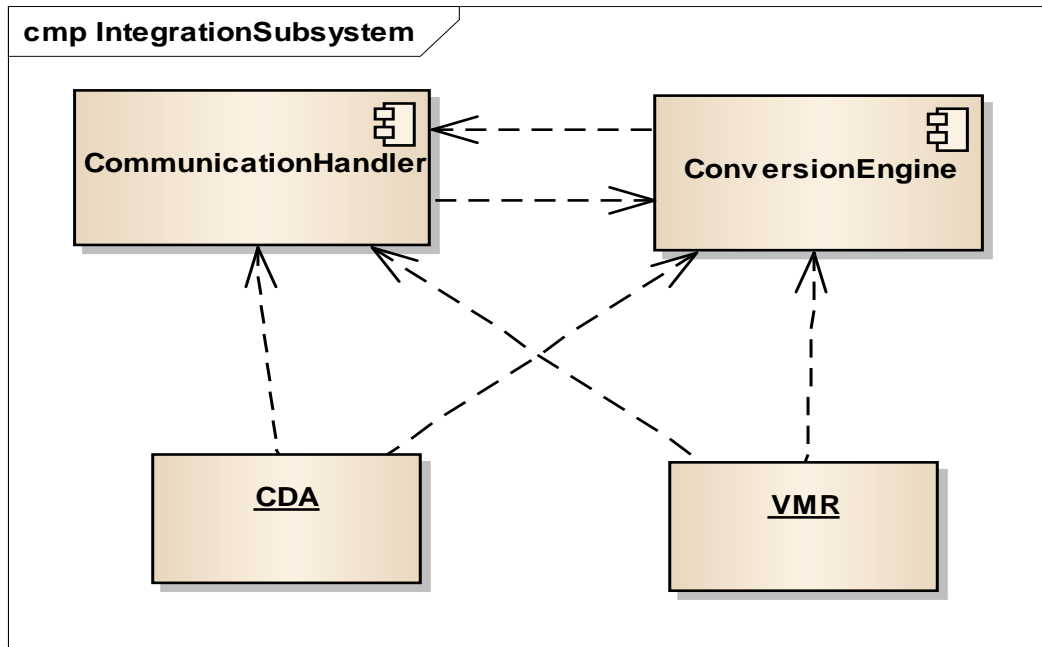
ConversionEngine is the subcomponent of IntegrationModule component and is used to transform standard format from HMIS compliant standard to PULSE compatible standard and vice versa.

- **CDA Object**

CDA Object is the standard format that is required by the HMIS to understand. Initially the HMIS provides CDA instance to PULSE and later get guidelines in the same format.

- **VMR Object**

VMR Object is the standard format that the PULSE understands for processing. Therefore before processing the CDA format is converted to VMR and the guidelines are also generated in the same format.



Chapter 4: Standard based Reasoning

4.1 Motivation

Standard base reasoning provides mechanism to execute knowledge rules persisted in form of standard MLMs. It allows maintaining shareable knowledge base and executing domain workflows provided by domain experts. The reasoner has the capability to handle event and data driven intervention provided by domain expert. It gives physicians to enhance knowledge base according to their requirements with minimal efforts.

4.2 Goals

- Constructing standard base domain knowledge for sharing among diverse organization.
- Standard base reasoner allows unify interfaces to manipulate knowledge rules representing domain expertise of physicians.
- Provide capability to fetch medical data required for decision making from diverse data source using standard vMR interfaces and generate standard base guidelines.

4.3 Related Work

The clinical decision support system (CDSS) has a strong history, starting in 1960 with stand-alone environments. With the advancement of architectural approaches and new requirements, CDSS has evolved from a stand-alone to a service-oriented architecture (SOA) environment. Moreover, for seamless integration of CDSS with existing health-care systems (EHRs, EMRs, PHRs, and CPOEs) to allow sharing of medical knowledge, various standards have emerged to achieve the desired goals. The most prominent knowledge representation language in the clinical domain is HL7 Arden syntax. Therefore, we will discuss the CDSS supporting Arden syntax as the main standard for the knowledge base.

Moni-ICU detects and continuously monitors nosocomial (i.e., hospital-acquired) infections. Moni-ICU uses a distinct approach by invoking a number of MLMs and implementing different rules that are controlled from one central MLM. The Moni-ICU application works in the ICU connected to a microbiology lab and a patient management system. It monitors all patients on a daily basis in each of the normal intensive care units, which comprise around 100 beds in total [Samwald2012].

Arden2ByteCode, a newly developed open-source compiler, runs on Java virtual machines

(JVM) and translates Arden syntax directly to Java byte code (JBC) executable. This compiler is integrated with SOA-based environments called open services gateway initiative (OSGi) platforms. The compiler has the capability to support all operators of Arden syntax and compile production Java bytecode in minimal time. Due to this direct byte code, the execution time of MLM is considerably reduced [Gietzelt2011].

Arden/J is a Java-based MLM execution environment that provides integration with XML-based and EMR systems and produces recommendations by executing MLM compiled to Java code. Arden/J supports a runtime environment that allows integration with other systems by implementing mapper interfaces. The authors claim good performance of the compiler and have tested it with XMLbased EMR [Karadimas2002].

4.4 Architecture

- **VMR Manipulator**

This module is used to process the vMR information. It is used to process vMR input and build vMR output. It consists of two modules: Extractor and Builder. Extractor is used to extract clinical information from vMR input and provides it to MLM Broker. Builder module is used to build vMR output after the MLM is invoked.

- **MLM Broker and MLM Meta Data**

MLM's are indexed in the MLM Meta Data module. Clinical information once extracted from the vMR by Extractor module is searched in the MLM Meta Data by the MLM Broker module.

- **MLM Invoker and MLM Repository**

If the MLM indexing information is obtained from MLM Meta Data, MLM invoker is provided this information which invoked the actual MLM from the MLM Repository.

- **VMR Repository**

VMR Input and vMR output are stored in the VMR Repository for future purposes.

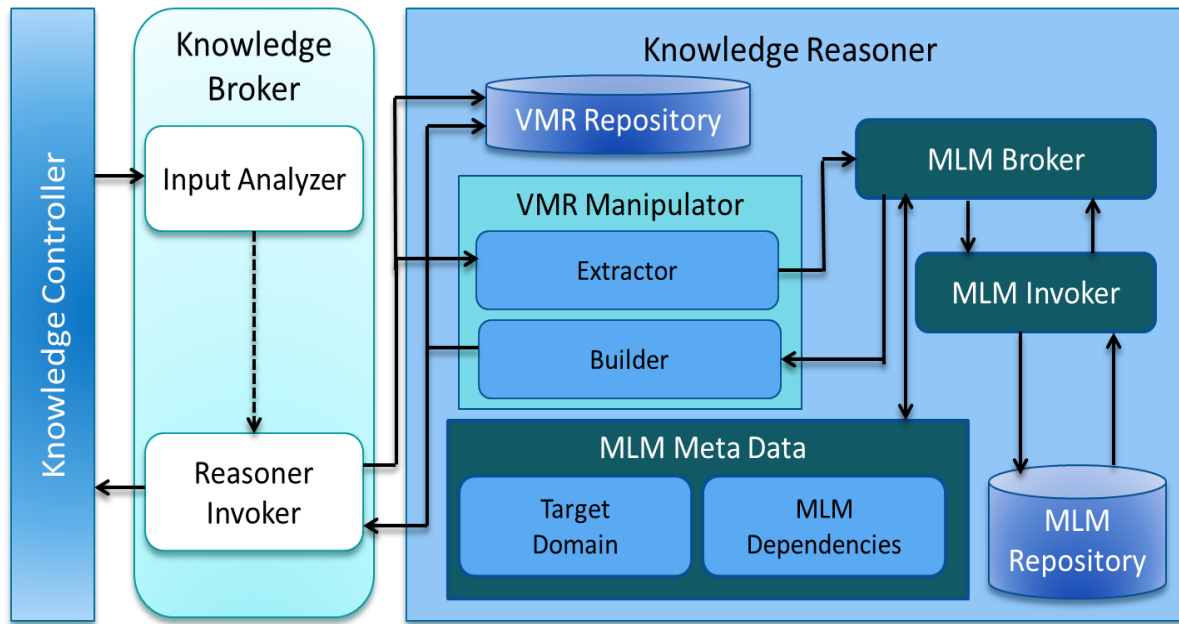


Figure 4.1: Standard based Reasoner Architecture

4.5 Uniqueness

- VMR based reasoning provisioning on clinical datasets
- Support for extension of multiple knowledge bases
- Evolution of clinical knowledge bases
- Maintenance and verification of clinical knowledge bases

4.6 UML Diagrams

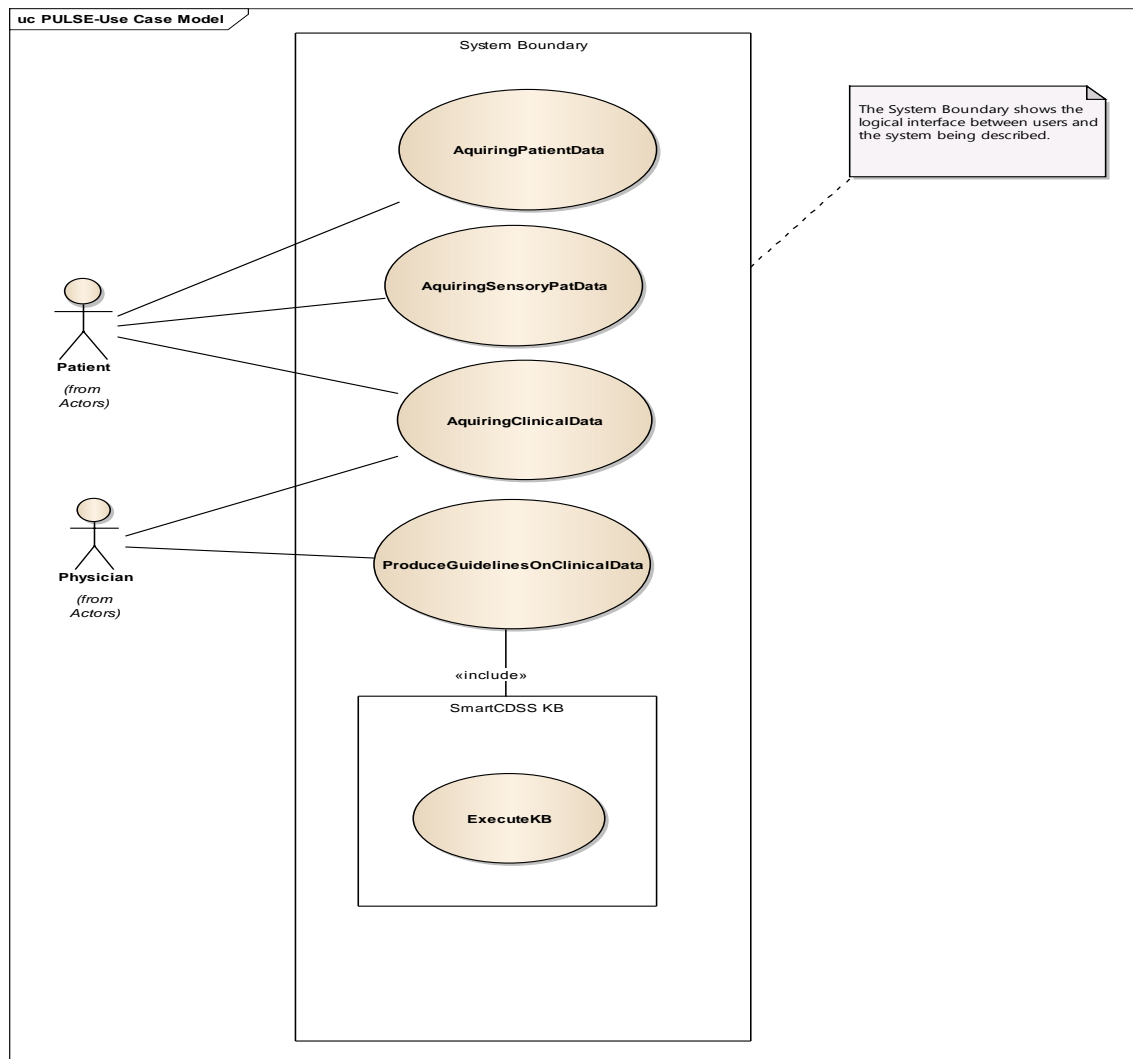
4.6.1 User Classes and Characteristics

Actors

- **Patient**
 - Patient is responsible to provide the social media data, his/her data is also collected using sensors, his behavior data and clinical data.
- **Physician**
 - Physician interacts with the system by entering the required data that is converted to HMIS compliant standard format.

4.6.2 PULSE-Chronic Disease Primary Use Case Model

Use Case Description



- **Acquiring Clinical Data**

Acquiring Clinical Data use case is used for obtaining the clinical data of the patient from the HMIS. This includes patient observations.

- **Acquiring Patient Data**

Acquiring Patient Data use case collects patient data from clinical information and also from social media.

- **Produce Guidelines on Clinical Data**

Produce Guidelines on Clinical Data use case is used for proving guidelines based on the clinical data that consists of clinical observations.

- **Execute KB**

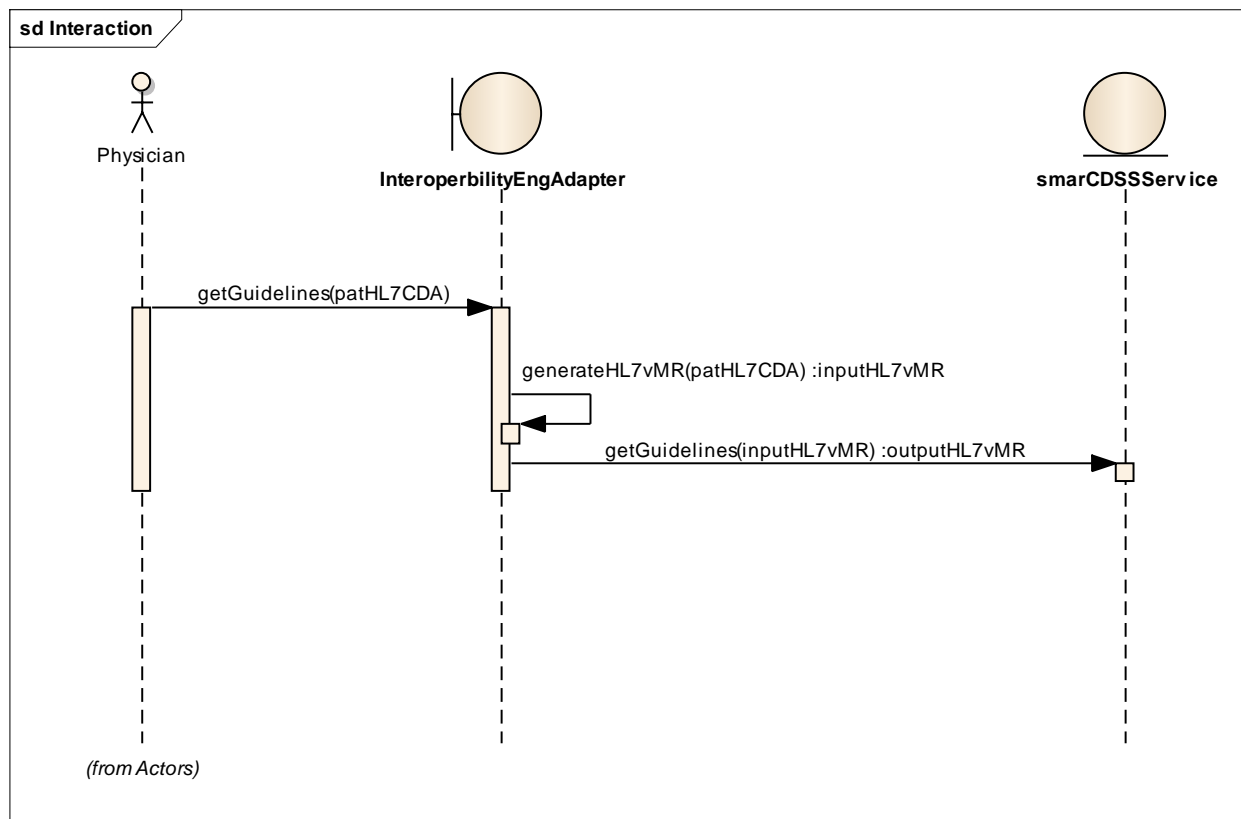
Execute KB use case stores all the rules in the knowledge base that needs to be fired when recommendations required to be generated.

4.6.3 Interaction Model

Sequence diagrams are described as follows that shows the interaction between different objects. PULSE-Chronic Disease overall sequence diagram is as follows:

PULSE-Chronic Disease Overall Sequence Diagram

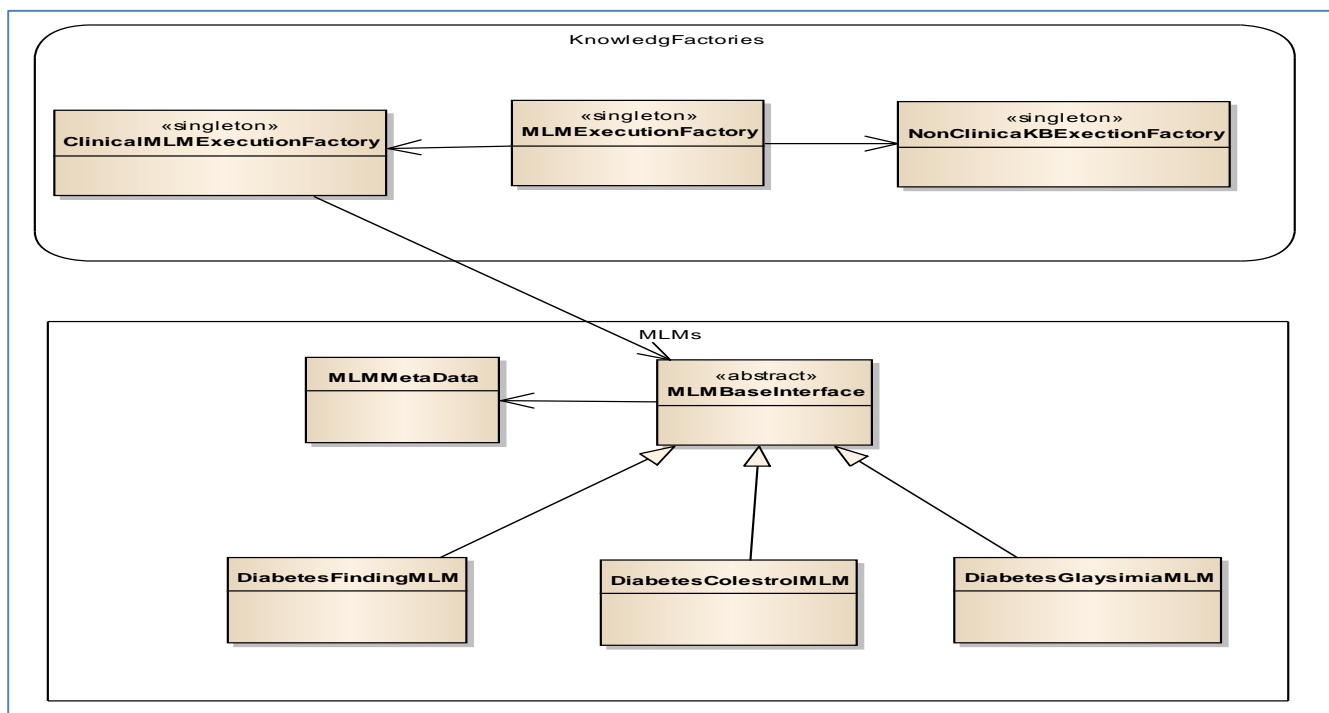
- Smart CDSS consumer applications such as HMIS generate an event and submit it to Smart CDSS for possible recommendations.
- InteroperabilityEngAdapter interface convert the HMIS input such as HL7 CDA into standard vMR format.
- Smart CDSS service is activated and based on clinical knowledge produce appropriate recommendations.



- The recommendations are send back in standard vMR output, where InteroperabilityEngAdapter translated to targeted consumer application.

4.6.4 Class Diagram

PULSE-Chronic Disease class diagram shows how the different classes relates with each other to provide appropriate guidelines to the physicians. Medical Logic Modules (MLM) are the standard format for generation and storage of rules in Arden Syntax. These MLMs store the logic behind the rule to be fired. These are stored in the Knowledge Base. Therefore the classes are divided on the bases of MLM distribution in the knowledge base. Factory Design pattern is shown in the class diagram that shows MLMExecutionFactory class. This class is based on clinical and non-clinical information, to decide which reasoned needs to be invoked for recommendation generation. Clinical information is represented by ClinicalMLMExecutionFactory class while the non-clinical information is represented by NonClinicalKBExecutionFactory class. ClinicalMLMExecutionFactory class is related with MLMBaseInterface abstract class. Different classes are inherited from MLMBaseInterface class based on the logic stored in each MLM class. These includes DiabetesFindingMLM class that is used to find whether the patient has diabetes or not; the DiabetesCholestrolMLM class that is used to find about the problem in the cholesterol level of the patient; and finally DiabetesGlycaemiaMLM that is used to find whether the patient has glycaemia or not. Also there is MLMMetaData class related with MLMBaseInterface class that is used to store annotations about each MLM stored in the knowledge base for easy retrieval.



4.6.5 Description of Components

The component diagram of PULSE-Chronic Disease shows the different components and their subcomponents interactions with each other. These are explained as follows:

- **EMR**

This component is used to provide clinical data in HMIS compliant standard format. It consists of subcomponent to generate the standard format. CDA Generator is the subcomponent used for generation of CDA format instance of the patient clinical information.

- **Authoring Tool**

This component provides the facility to physicians to enter their knowledge into the knowledge base that will become the rules for recommendations to be provided. These consist of subcomponents like: Guideline Publisher and Knowledge Validator.

- **Interface Engine**

This component is used to behave as bridge between adaptability engine and knowledge inference engine. It takes input from the adaptability engine and provides to knowledge inference engine from processing. Finally it takes the recommendations from knowledge interface engine and provides it to adaptability engine. It also provides subscription facility to authorized users. All these functions are performed by subcomponents of these components that are: Standard Input Interface, Standard Output Interface, and Subscription Service.

Chapter 5: Feedback Analysis

Module

5.1 Feedback Analyzer

5.1.1 Motivation

Interaction with users and getting their feedback is necessary step to evaluate our system. Feedback Analyzer module provides the evaluation scheme to identify users feedback, and improve system performance accordingly. Users or patient can specify their satisfaction and dissatisfaction over the recommendations provided by the system. If a specific number of users are not satisfied with the recommendations for particular system, experts are notified for evolution of the not satisfactory rules in the knowledge base. Feedback Analyzer provides the interface to users for interaction with the system and evaluating the system performance.

5.1.2 Goals

- Provide interaction platform to users for feedback provision on system's recommendations
- Evaluating system performance based on user's feedback
- Evolution of rules based on satisfaction of the users
- Easy for experts to evaluate and evolve rules into the systems

5.1.3 Architecture

- **Feedback Editor**

Feedback Editor is used for obtaining user feedback after the recommendations are provided to the patients. It consists of two sub modules:

- User Evaluation

It provides user free text editing environment where the patient can express his reaction to the recommendations provided and adopted by him/her. The patient can help in improvement by stating the problems faced due to system's recommendations or the cure that it provides. This will help the expert in evaluating the rules that needs revision.

- Confidence Value

Based on the outcome of the recommendations implementation on user, the user can provide confidence value about the recommendation. This will help in

evaluation of the rules and would expose the rules that are not effective and needs modifications.

- **Feedback Repository**

The information about the user evaluation and confidence value is stored in the feedback repository that can be used for knowledge base evolution and also trusted network build.

- **Knowledge Base Evolution**

Continues monitoring of the feedback would lead to improvement in the rules stored and thus evolving knowledge base. It consists of the following two sub modules:

- Confidence Value Monitor

This module monitors the confidence values for particular recommendation given by specified number of users. A threshold value n is set and evaluation of the specified number of users' m is monitored and value is calculated. For every m number of users the threshold value is calculated and checked with n threshold value.

- Expert Notification

If the average confidence value for m users is less than threshold value n , then expert is notified to evaluate the current rule as most of the users are not satisfied with the rules. The expert based on the feedback will decide whether the rule needs to be changed or not.

- **Alert Manager**

- Detect User

Once a new user is detected or some user wants to get trusted network information, this module will forward the information to TRIM module for processing.

- Recommendation Info

The users' information that includes his demographics, symptoms and recommendations information is forwarded to the TRIM module for further processing.

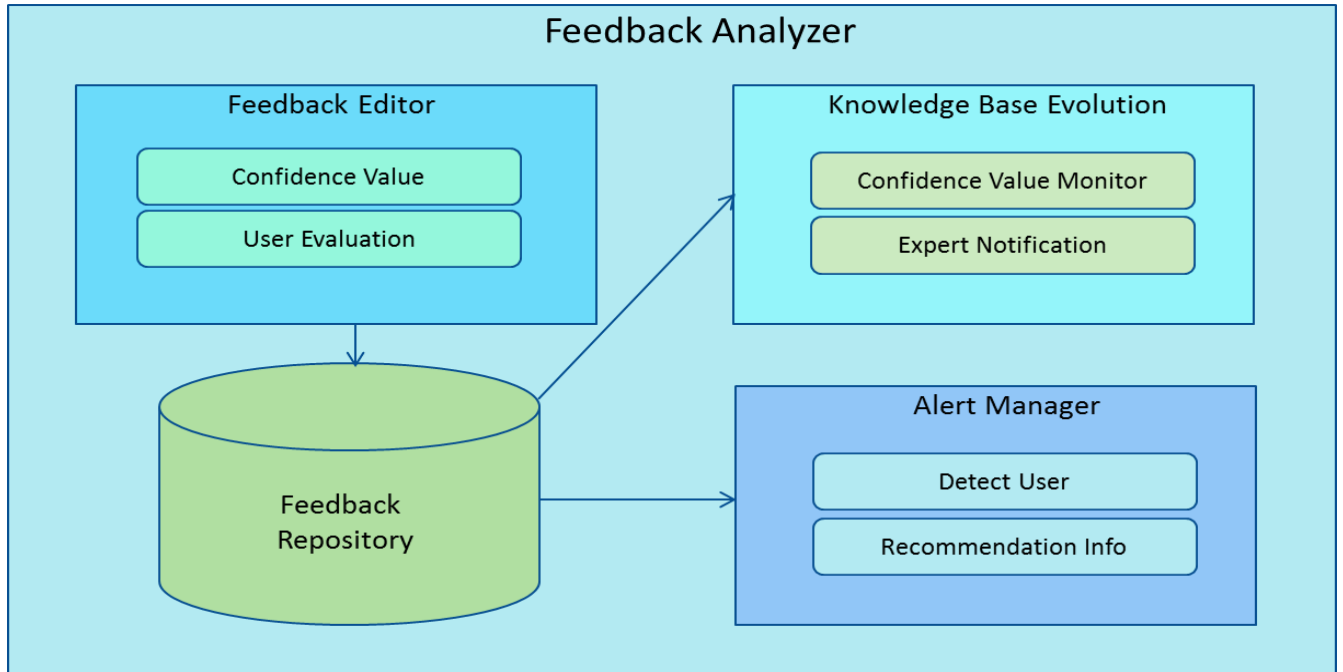


Figure 5.1: Feedback Analyzer Model

5.2 Trust-Aware Life-care Recommendation Improvement Model using Patient Feedbacks (TRIM)

5.2.1 Motivation

When get the chronic recommendations given by the system, the users may probably give some feedback: whether they like the recommendations, or whether there are some users whose feedback they continuously found useful. By mining this valuable feedback information, it is possible to find the preference of each user. This helps the system to recommend the most acceptable recommendations to each user. In addition, when joining the system, some new users may not give any feedback. This may because they are not familiar with the system or just because they have not started using the system yet. These new users are the key to expand the usage of system, especially in real applications. The feedback manager proposed in this project motivates to:

1. Provide the most acceptable chronic recommendations to new users of the system, helping them find their favorite recommendations rapidly.

2. Provide the reliable personalized recommendations to existing users of the system effectively and efficiently.

5.2.2 Goals

The goal of the feedback manager is to mining users' feedback on the chronic recommendations and users' feedback on other users in the system, find users' preferences and the acceptance level of the recommendations, and then provide the most acceptable chronic recommendations to users.

5.2.3 Related work

The most popular way to mining user feedback to find their preferences is the collaborative filtering (CF). CF is the method that filters information based on the preferences of users. Two users' common preferences are calculated based on their similarities. The user similarity is calculated by comparing the ratings these two users gave on their co-rated items. The recommendations liked by one user are regarded as more acceptable by users who have similar preferences.

The advantage of CF is that it has high accuracy and it can be easily applied in the real applications. However, it has its own limitations. Firstly, it suffers from the well-known data sparseness problem: the scale of the real application is always very large, yet the number of items rated by each user is always limited compared with the total number of items, so it is sometimes very hard to find the co-rated items by two users. This makes it difficult to calculate the user similarity between two users. Since user similarity is the basis of CF, CF cannot give personalized recommendations in this situation. Secondly, CF suffers from the cold start problem. The cold start problem means some new users have not given any ratings or only given very limited number of ratings. In this case, it is hard for CF to find these new users' preferences and give reliable recommendations.

To solve the problems of CF, trust-aware recommender system (TARS) has recently been proposed for use. TARS improves the conventional CF by giving the recommendations based on user trust instead of user similarity. Trust is measure of willingness to believe in a user based on its competence and behavior within a specific time. The basic property of trust is that trust is transitive. This means if A trusts B and B trusts C (A and C do not have direct trust), A will trust C to some extent. So even if two users do not have direct relations in the feedback network, it is

possible to build up some indirect relationships based on trust propagations. It has been verified that TARS has similar recommendation prediction accuracy as CD, while the recommendation prediction coverage can be much improved. In addition, it is shown that TARS can effectively deal with the data sparseness problem and the cold start problem, which are the bottleneck of CF.

Though TARS has been verified to be effective and efficient in giving recommendations, existing models of TARS also have limitations. Firstly, existing TARS models cannot give recommendations for those who did not give any feedbacks. Existing TARS models provide personalized recommendations, so users should at least point out their feedback on at least one user in the feedback network. Otherwise, it is impossible for existing TARS model to give recommendations. Secondly, the efficiency of existing TARS models should be further improved. The computation complexity of TARS mainly in the computation of searching recommenders for the active users in feedback network. Existing models fully search the feedback network to find recommenders, the computation complexity is $o(k^d)$, where k is the average degree of the feedback network, and d is the maximum allowable trust propagation distance. The computational complexity should be further reduced.

5.2.4 Architecture

Feedback is be used to improve the rule of the inference engine, it can also be used to improve recommendations of PULSE, as shown in Fig. 5.2, helping PULSE provide the most acceptable recommendations to users.

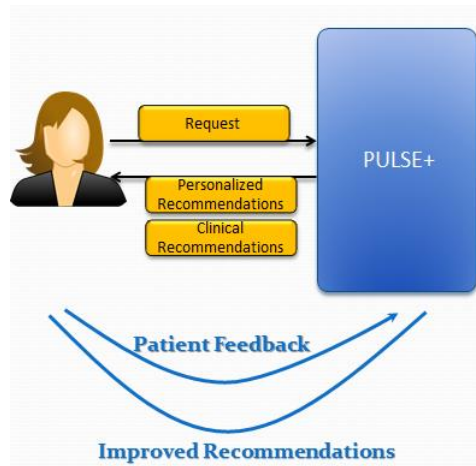


Figure 5.2. Feedback used in PULSE.

In PULSE feedback manager, we mainly use two kinds of feedback, as shown in Fig. 5.3. One kind of feedback is the feedback on recommendations given by PULSE. E.g., the users can point out whether they are satisfied with the recommendations. The other kind of feedback is the feedback given on the users of PULSE. If a user finds another user's feedback on recommendations is continuously helpful, he can give explicit feedback on the trustworthiness of this user: he can point out that he trust this user.

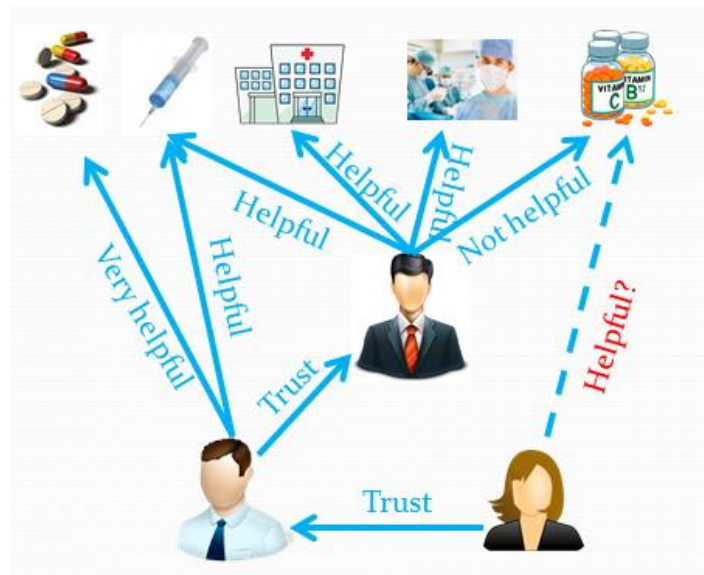


Figure 5.3. Feedback used in feedback manager.

The overall architecture of feedback manager is given in Fig. 5.4. The feedback is involved in feedback manage via User Feedback Analyzer. Two kinds of feedback, i.e., the user trust and the ratings on recommendations are stored in User Trust Repository module and Recommendation Repository module respectively. There are mainly two function modules in feedback manager: Global Recommendation Predictor module and Personal Recommendation Predictor module. The Global Recommendation Predictor module is used to provide the most acceptable recommendations to the new users of PULSE. In this case, the new users can benefit from the feedback given by other users, and find the most popular and most acceptable recommendations. This helps them involve in the feedback network more rapidly. The Personal Recommendation Predictor Module is used to provide the personalized recommendations for those who have already

given their feedback. By mining their feedback and the feedback given by other users in the feedback network, PULSE can recommendation more personalized recommendations to users.

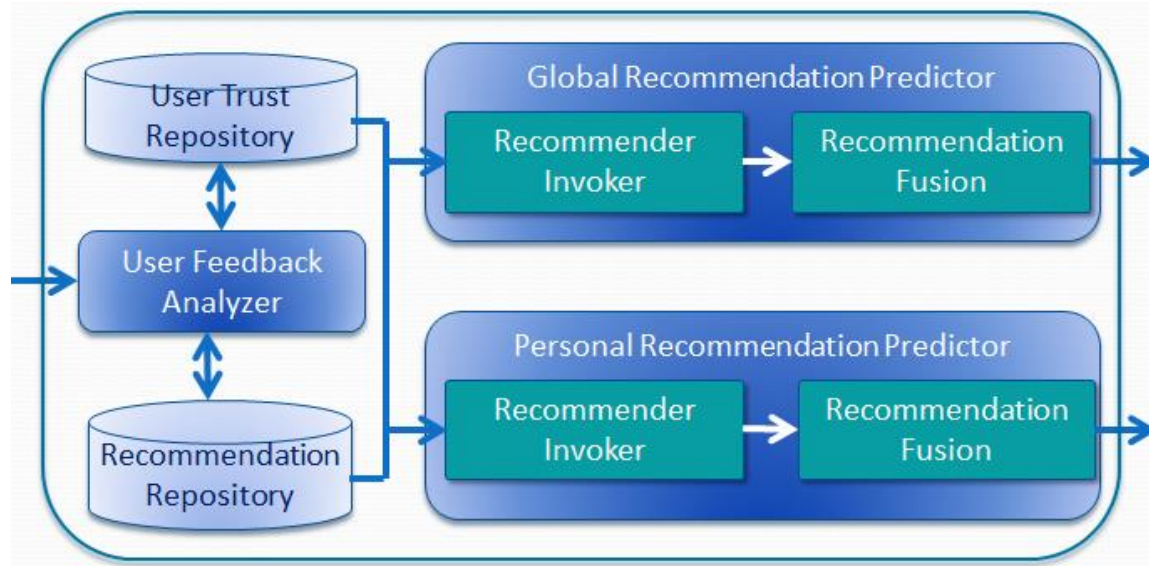


Figure 5.4. The overall architecture of feedback manager model.

Two modules are involved in Global Recommendation Predictor module and Personal Recommendation Predictor module respectively: Recommender Invoker module and Recommendation Fusion module. The Recommender Invoker module is used to find the suitable recommenders for the active users. In Global Recommendation Predictor module, Recommender Invoker module is used to find the most reputable recommender in the feedback network. In Personal Recommendation Predictor module, Recommender Invoker module is used to find recommenders in each users own personal trust network. Since existing TARS model is not efficient in searching recommenders, Recommender Invoker module in Personal Recommendation Predictor mainly focus on reducing the computational complexity of recommender searching. Recommender Fusion module in both Global Recommendation Predictor module and Personal Recommendation Predictor module are used to aggregate the recommendations given by Recommender Invoker.

5.2.5 Uniqueness

The uniqueness of feedback manager is mainly focus in two aspects:

1. We provide efficient recommender searching mechanism, which computational much less expensive than existing works. This is achieved by (1) mining the patient feedback network with less computational complexity, and (2) provide reliable globalized recommendation mechanism to new users
2. We suggest the most acceptable recommendations to new users, i.e., recommendations given by the most reliable users in the patient feedback network. This can helps new users involved in PULSE more rapidly.

5.2.6 UML diagrams

User Classes and Characteristics

Actors

1. Patient

Patient is responsible to provide the feedback information, including (1) the feedback on the chronic recommendation, e.g., helpful, somewhat helpful, not helpful etc., and (2) the feedback on other patients: if they find the feedback given by a patient continuously helpful, they can explicitly point out their trust on this user, e.g., trust, distrust etc.

2. User Feedback Analyzer

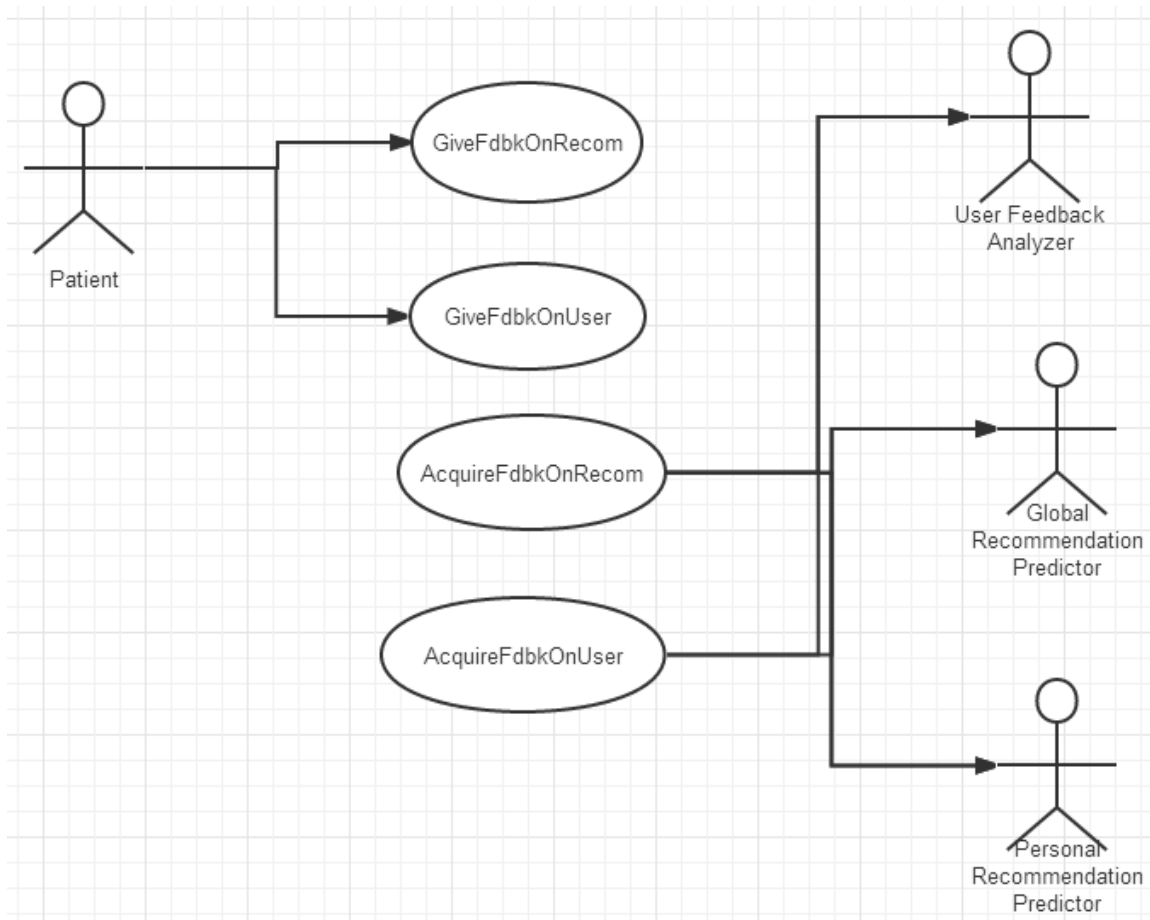
User Feedback Analyzer gets information from patients, and stores the information in the repository. It is the interface of Feedback Manager and other parts of PULSE.

3. Global Recommendation Predictor

Global Recommendation Predictor is used to suggest recommendations for those who have not given any feedback. It extracts feedback information from the related repository.

4. Personal Recommendation Predictor

Personal Recommendation Predictor is used to suggest recommendations for those who have already given feedback. It extracts feedback information from the related repository.



User Case Description

- **GiveFdbkOnRecom**

GiveFdbkOnRecom use case is used for giving feedback on the chronic recommendations. After patients get the recommendation given by PULSE, they may give some feedback on this recommendation: whether they are satisfied with this recommendation or not.

- **GiveFdbkOnUser**

GiveFdbkOnRecom use case is used for giving feedback on the patients of PULSE. In PULSE, the patients' feedback on the recommendations is public. If one user finds another user's feedback on recommendations is continually helpful, he can explicitly point out his trust on this user.

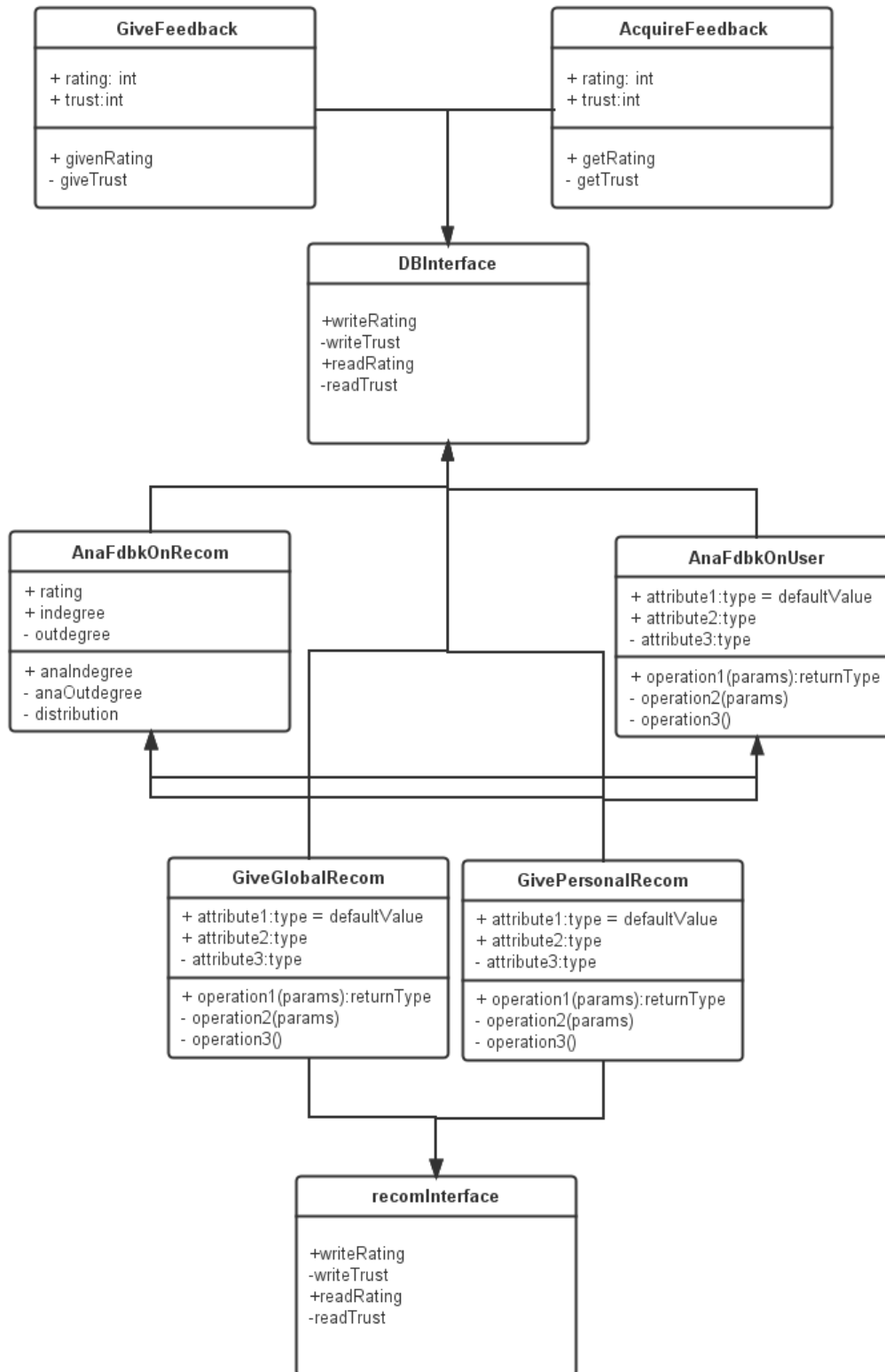
- **AcquireFdbkOnRecom**

AcquireFdbkOnRecom use case is used for getting patients' feedback on recommendations given by PULSE. The feedback on recommendations is used to verify the reliability and the acceptance level of these recommendations.

- **AcquireFdbkOnUser**

AcquireFdbkOnUser use case is used for getting patients' feedback on other patients involved in PULSE. This feedback information is used to verify the reliability and trustworthiness of other patients. For those who have not given any feedback in PULSE, recommendations given by the highly trusted patients will be suggested. For those who have already given their own feedback on other patients, their personal trust networks are built and personalized recommendations are suggested based on these personal trust networks.

Class Diagram



The class diagram of Feedback Manager includes 6 classes and 2 interfaces.

- GiveFeedback

GiveFeedback class is used to write the recommendation repository and user trust repository. There are mainly two operations: one is used to give feedback on the recommendations given by PULSE; the other one is used to give user trust on other patients involved in PULSE.

- AcquirFeedback

AcquirFeedback class is used to get the feedback information from the recommendation repository and user trust repository. Users can use this class to get the concrete user feedback information. There are mainly two operations: one is used to get feedback on ratings on recommendations; the other one is used to give user trust on other patients involved in PULSE.

- DBInterface

DBInterface interface is used to read and write the recommendation repository and user trust repository.

- AnaFdbkOnRecom

AnaFdbkOnRecom class is used to analyze the ratings on the recommendations, which is stored in recommendation repository. Indegree and outdegree of the rating matrix are analyzed to get the statistical information, which can be used in the further recommendation.

- AnaFdbkOnUser

AnaFdbkOnUser class is used to analyze the user trust given by each user in PULSE. The goal is build up each user's own personalized trust network. Further information of the trust network is analyzed, such as the trust propagation distance etc.

- GiveGlobalRecom

GiveGlobalRecom class is used to give recommendations to those who have not given any feedback in PULSE. This class will suggest the most acceptable recommendations. This will help the new users involve in PUSLSE more rapidly.

- GivePersonalRecom

GivePersonalRecom class is used to give recommendations to those who have already given any feedback in PULSE. This class gives the personal suggestions based on each

user's own trust network. Since trust is transitive, most users can build up their trust networks based on the trust propagations. So it is possible to provide the personal recommendations to most users who have involved in the feedback network.

- **RecomInterface**

RecomInterface interface is used to give the recommendations to users. The recommendations are provided by GiveGlobalRecom class for those who have not given any feedback in PULSE. The recommendations are provided by GivePersonalRecom class for those who have already given any feedback in PULSE.

Chapter 6: System Integration and Deployment

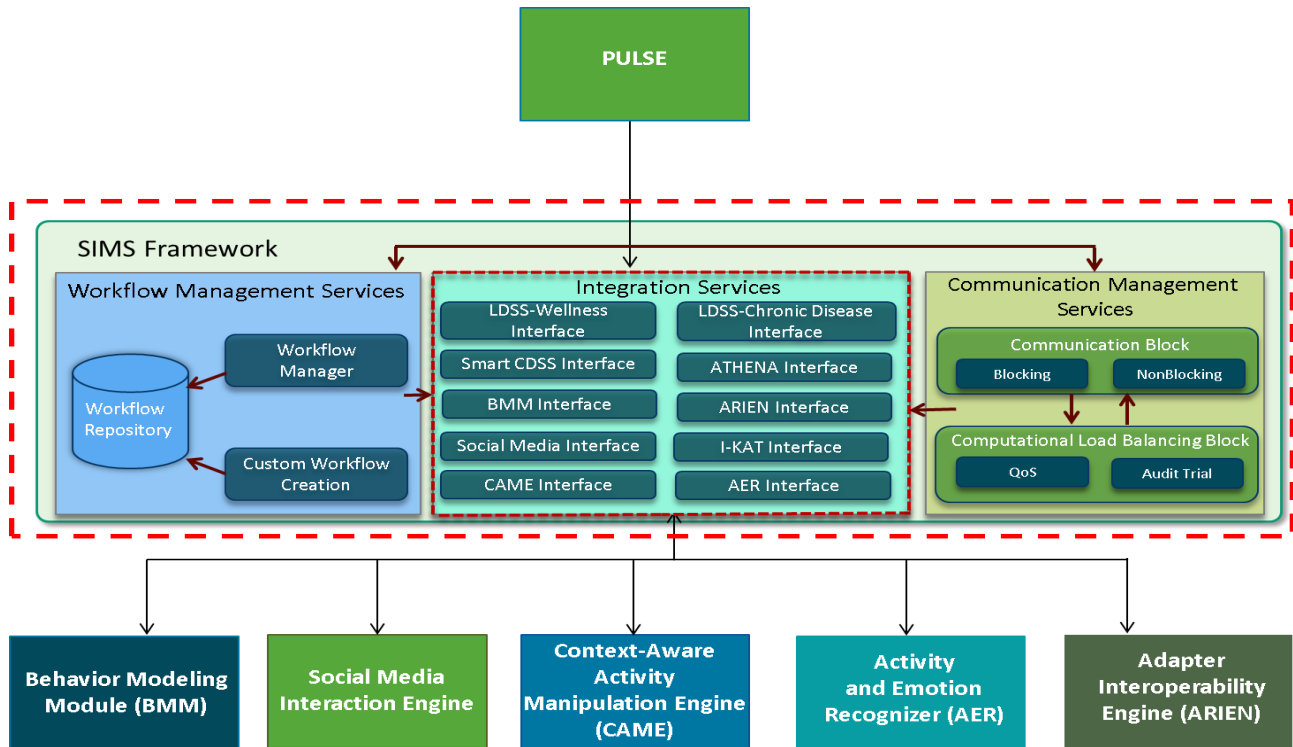
6.1 Motivation

PULSE system is dependent on external engines for processing of information from different sources. These engines provide processed information to PULSE for concatenation and guidelines or recommendations generation. This integration is performed using a centralized integration framework called System for Integration and Management Services (SIMS) framework. It behaves as a bus for communication between different external engines.

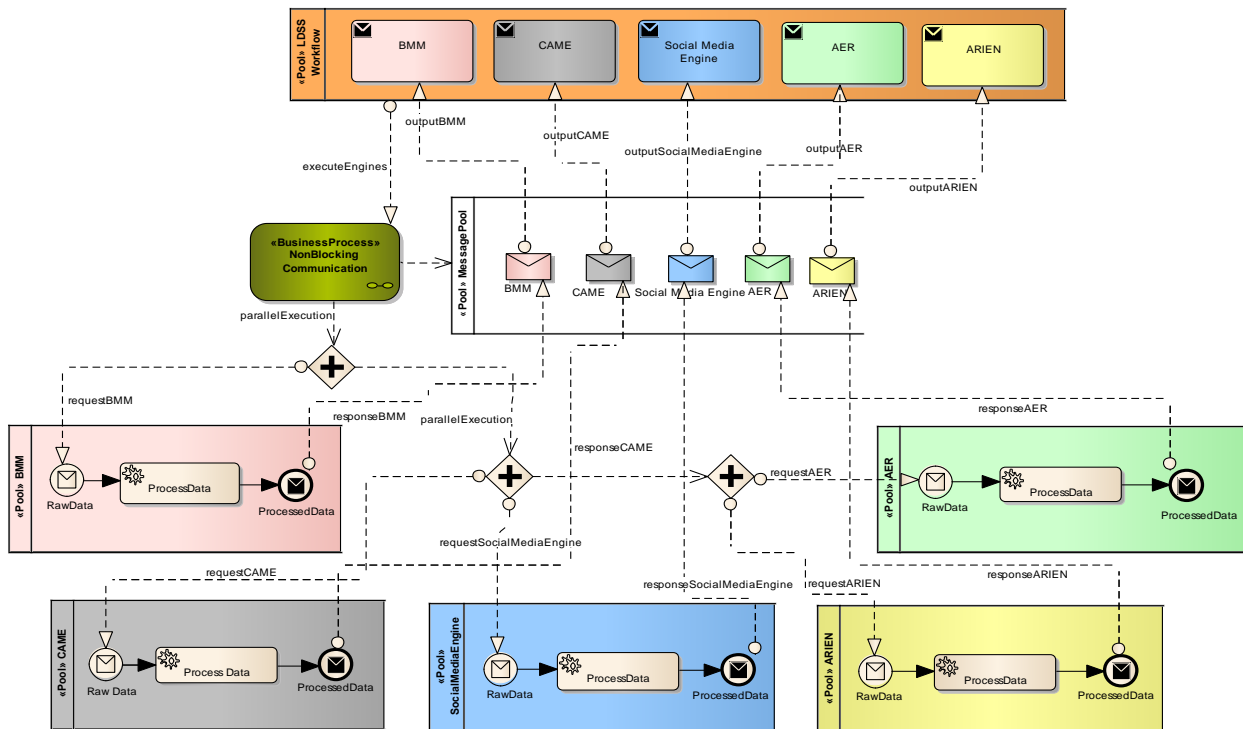
6.2 Goals

- SIMS framework behaves as a bus for communication of PULSE with AER, CAME, ARIEN, BMM and Social Interaction engine.
- Controls the overall flow of information and also provides load balancing services. It handles the non-blocking communication of different engines processing heterogeneous datasets.
- Provisioning of integration services for seamless communication through respective interfaces.

6.3 Architecture



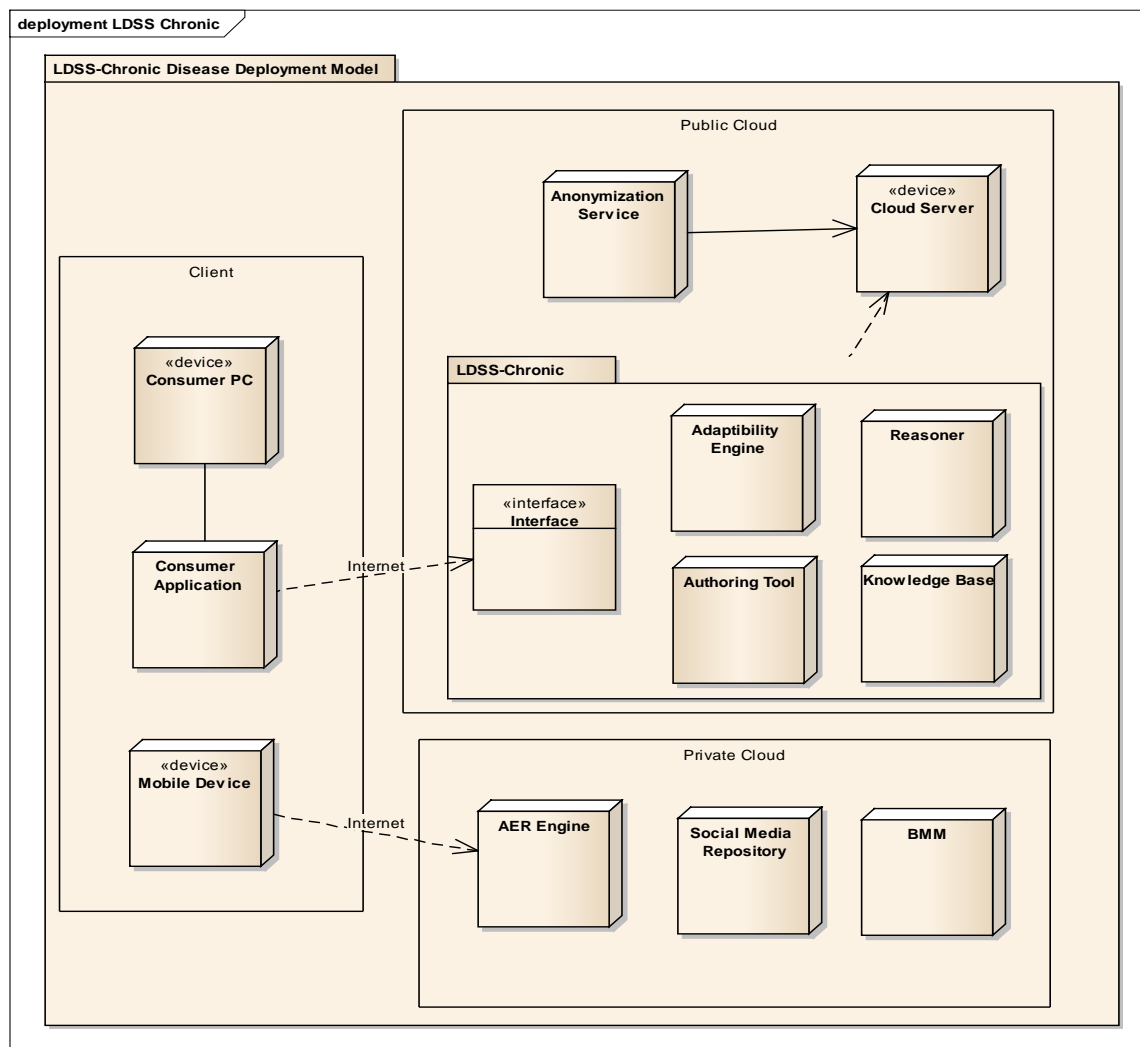
6.4 PULSE Workflow on SIMS Framework



6.5 System Deployment Diagram

The deployment diagram is divided into three layers client side, public cloud and private cloud. These are described as follows:

- Client side can access LDSS-Chronic Disease using Consumer PC, Consumer Application or Mobile Device.
- Public Cloud consists of Anonymization service and cloud server to secure and store data. Also LDSS –Chronic Disease is deployed on cloud, so its services can be easily utilized. The LDSS-Chronic Disease components deployed over cloud includes Adaptability Engine, Reasoner, Authoring tool and Knowledge Base.
- Private Cloud consists of components that are more sensitive that includes Activity and Emotion Recognizer activities analysis, social media repository and BMM.



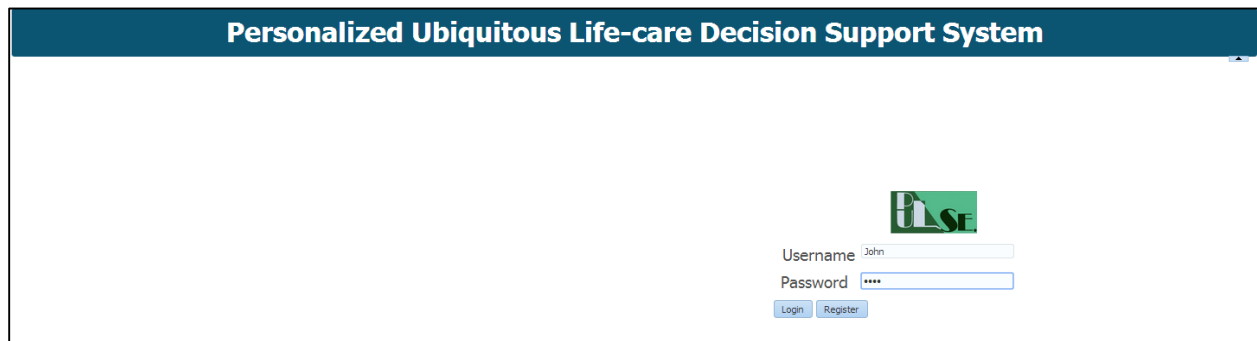
Chapter 7: Case Study

7.1 Overview


PULSE system for chronic disease monitors patient EMR data and personalized data to provide health analytics to the user. EMR data contains patient clinical observations, and PULSE monitors that data to find abnormal observations. Health analysis is also provided that shows the behavior of the observations during patient multiple encounters. This helps in identifying the observations that needs to be cured by changing lifestyle. The lifestyle changing information can be obtained by monitoring the personal activities of the patient. While EMR data monitoring and health analytics is part of the clinical recommendations, daily life activities monitoring and analytics relates to the personalized recommendations. The personalized data is monitored between different encounters and it includes specific activities monitoring. In the end, to evaluate the system and know about the patient satisfaction in using the system, feedback services are provided.

7.2 User Subscription and PULSE Services

The PULSE system can only be used by the user/ patient/ physician who is subscribed to the system. This helps in maintaining the security and privacy issues and allowing only the subscribed user to manipulate his/her data.



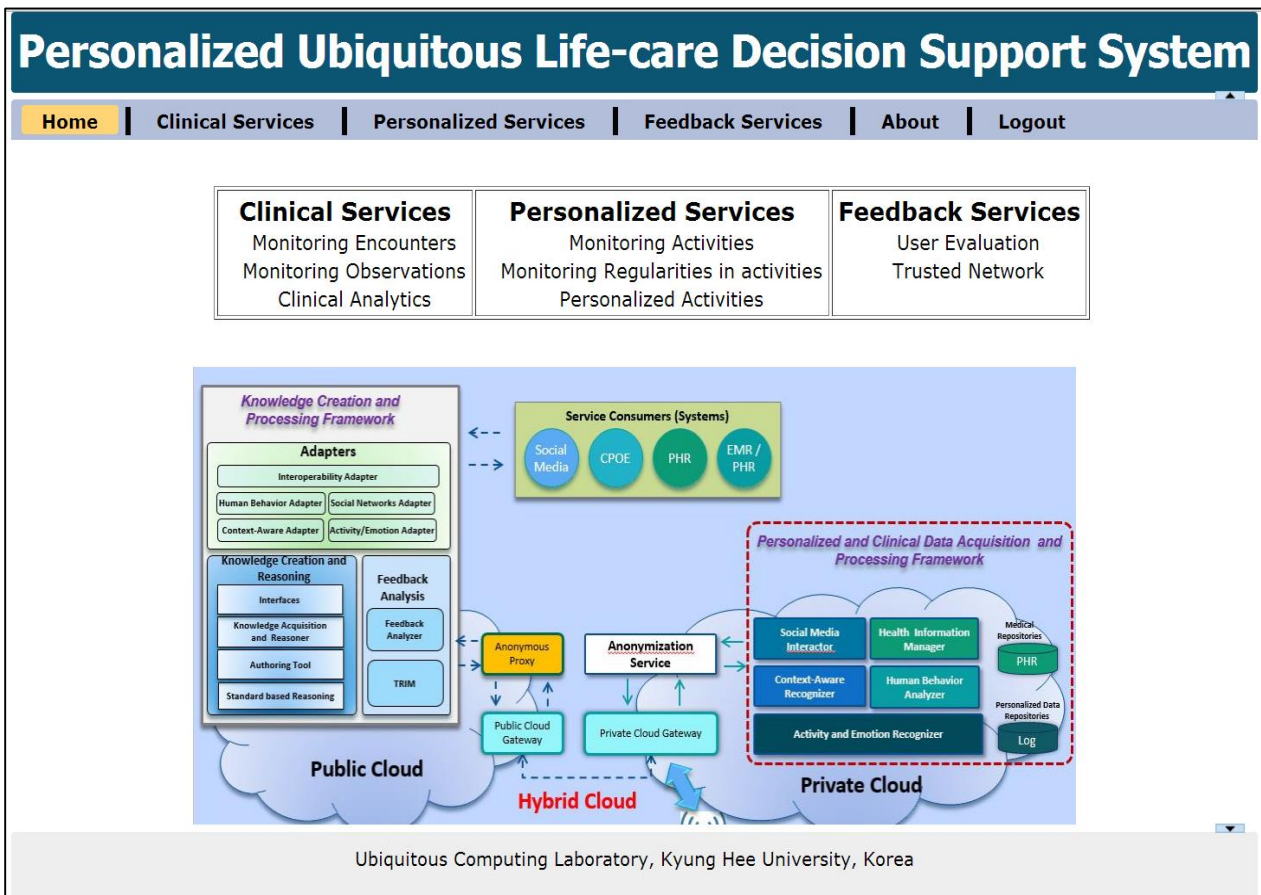
Personalized Ubiquitous Life-care Decision Support System



Username

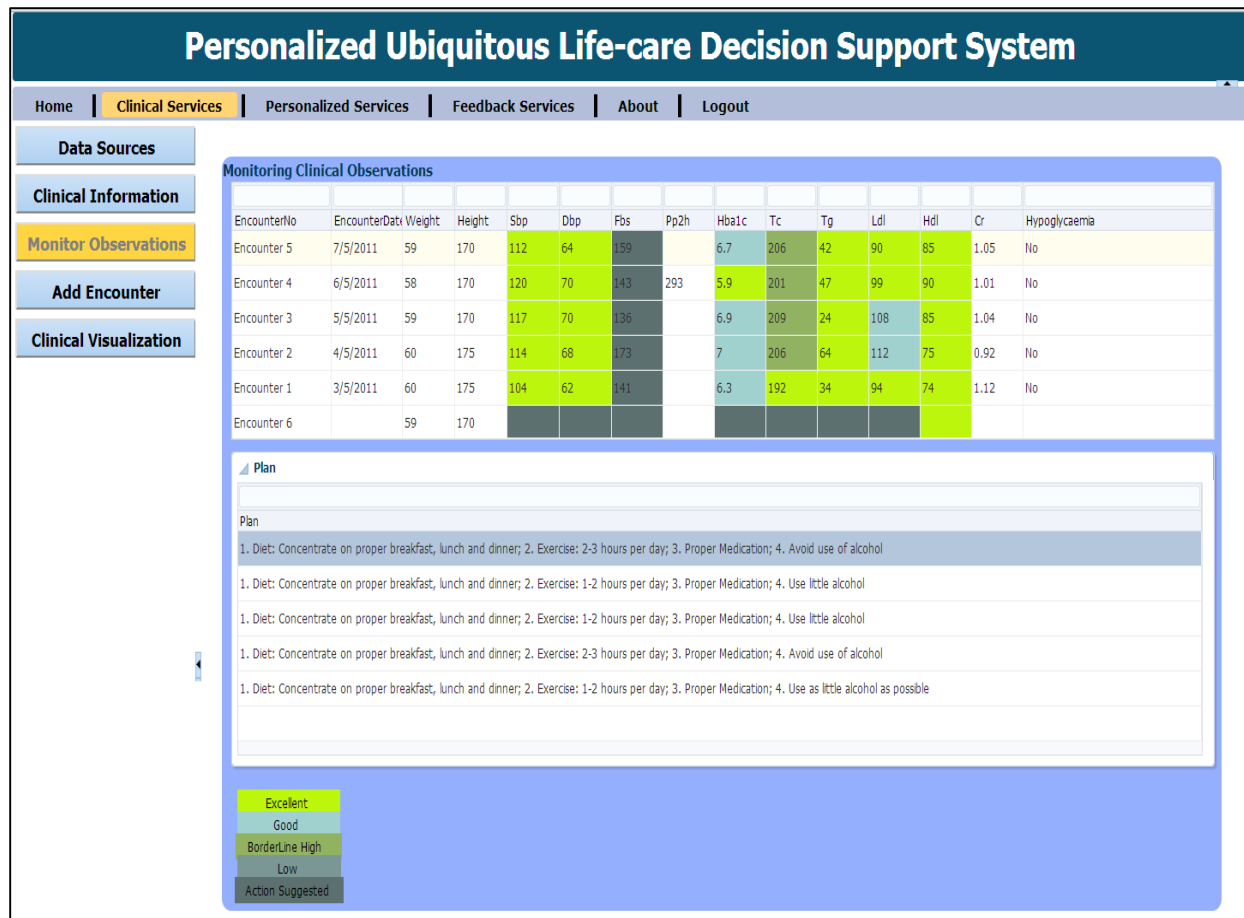
Password

PULSE provides clinical, personalized, and feedback services to the chronic disease patients. Clinical and personalized recommendations are in the form of health analytics while feedback services are used for evaluating the system and improving the system's functionalities and also building trusted network.

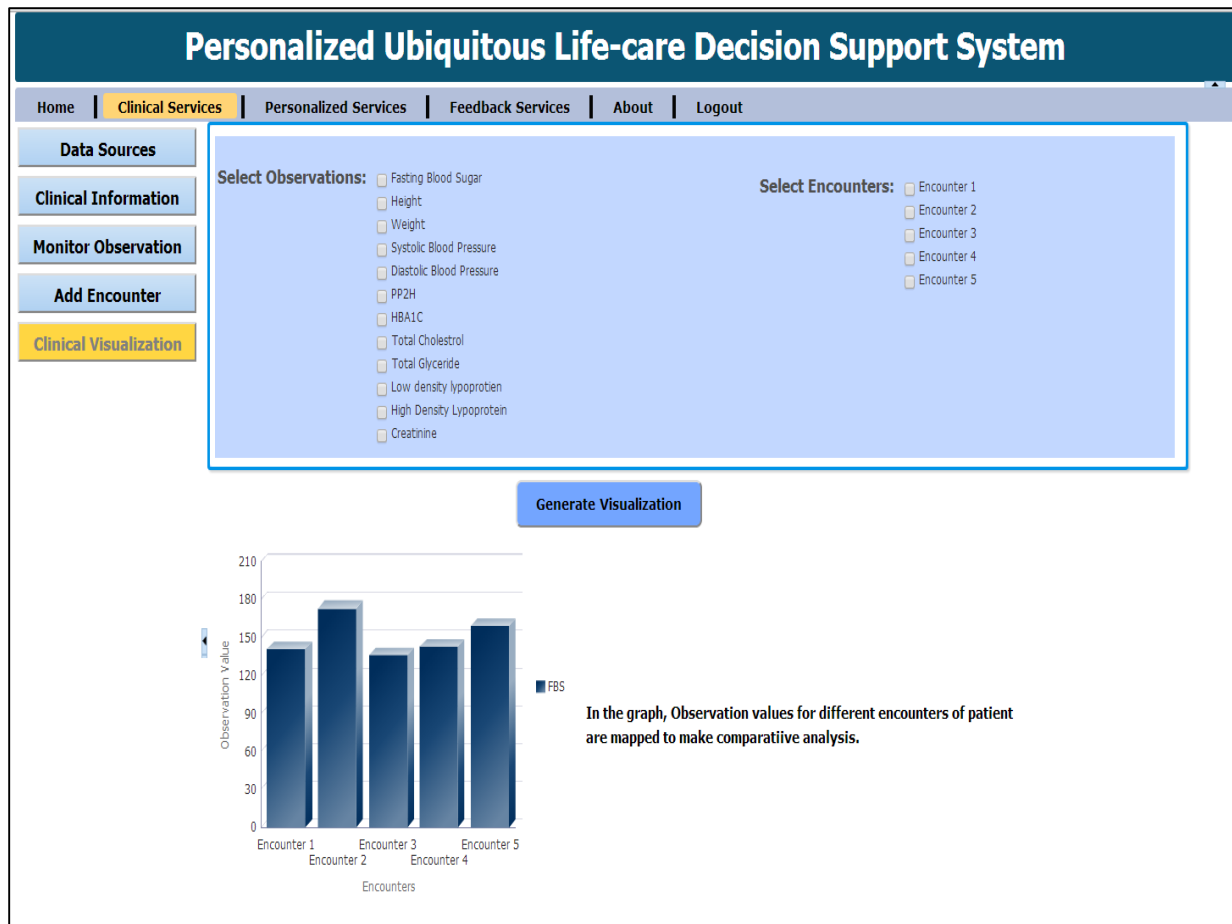


7.3 Clinical Services

The patient encounters data is monitored using MLM stored in the clinical knowledge base to identify abnormal observations. These observations are categorized into different colors to show the nature of the observations to the users. The different states of the observations shown with different colors that are found by the MLM includes Excellent, Good, Borderline High, Low and Action Suggested. The borderline high and action suggested states shows that the observations are abnormal and the user needs to change his life-style.

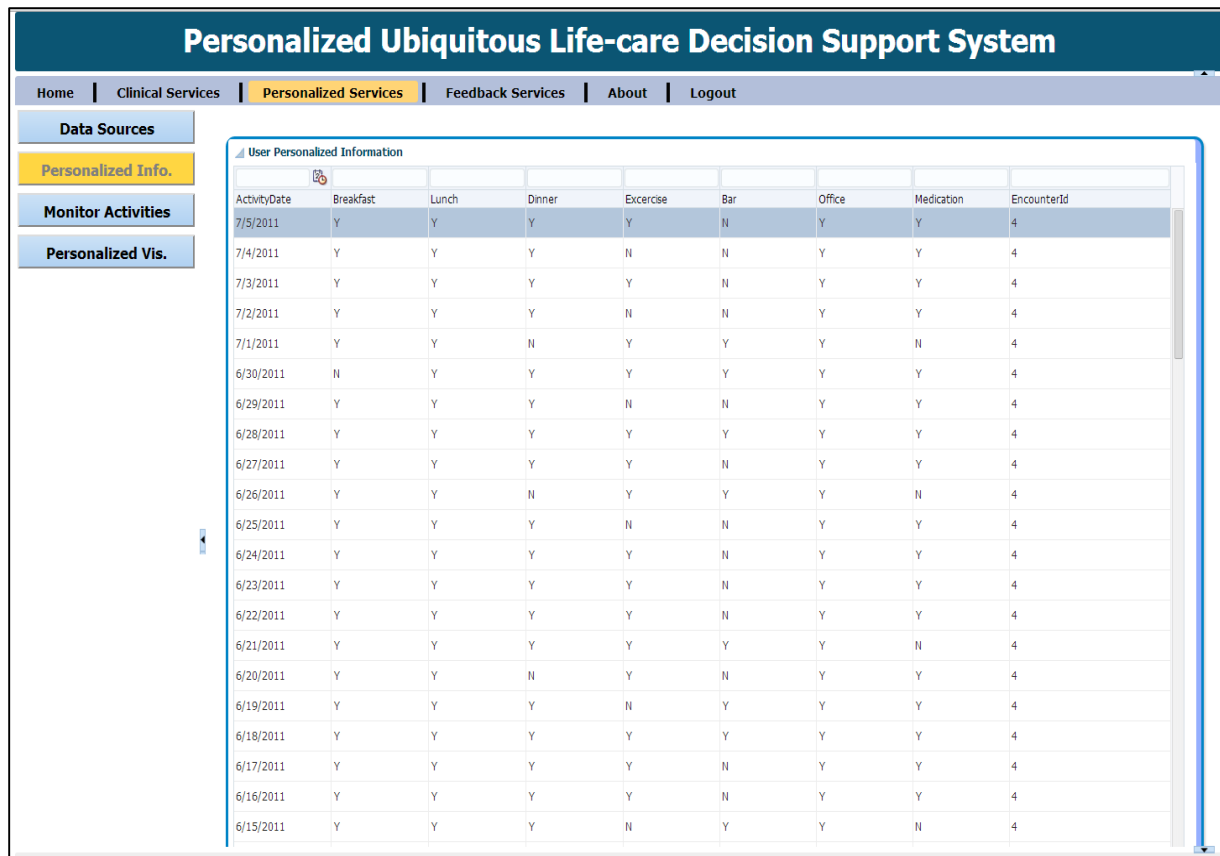


The clinical observations once monitored and the abnormal observations are identified, then the health analytics can visualize the patterns of changes that has occurred during different encounters of the patient. For example, in the current scenario, the Fasting Blood Sugar (FBS) value shows the abnormal behavior for the current patient with action suggested in each encounter. Also, it can be seen that the value of FBS has increased considerably between encounter 1 and 2. Therefore, the patient activities information in the duration of these encounters should be witnessed for lifestyle improvement of the patient.

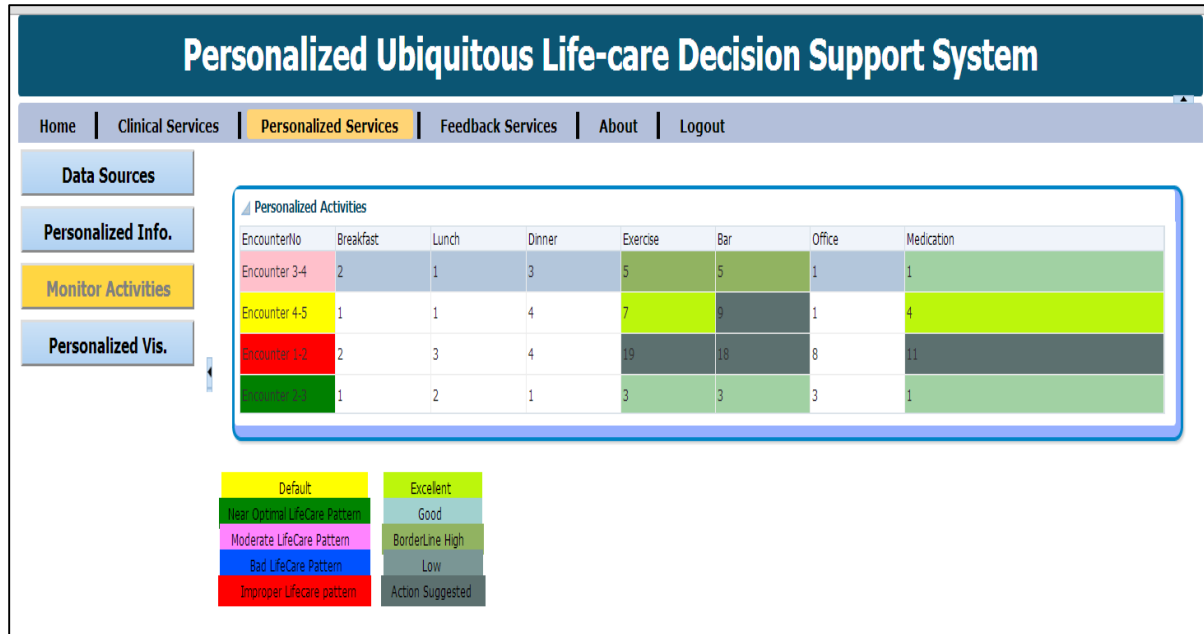


7.4 Personalized Services

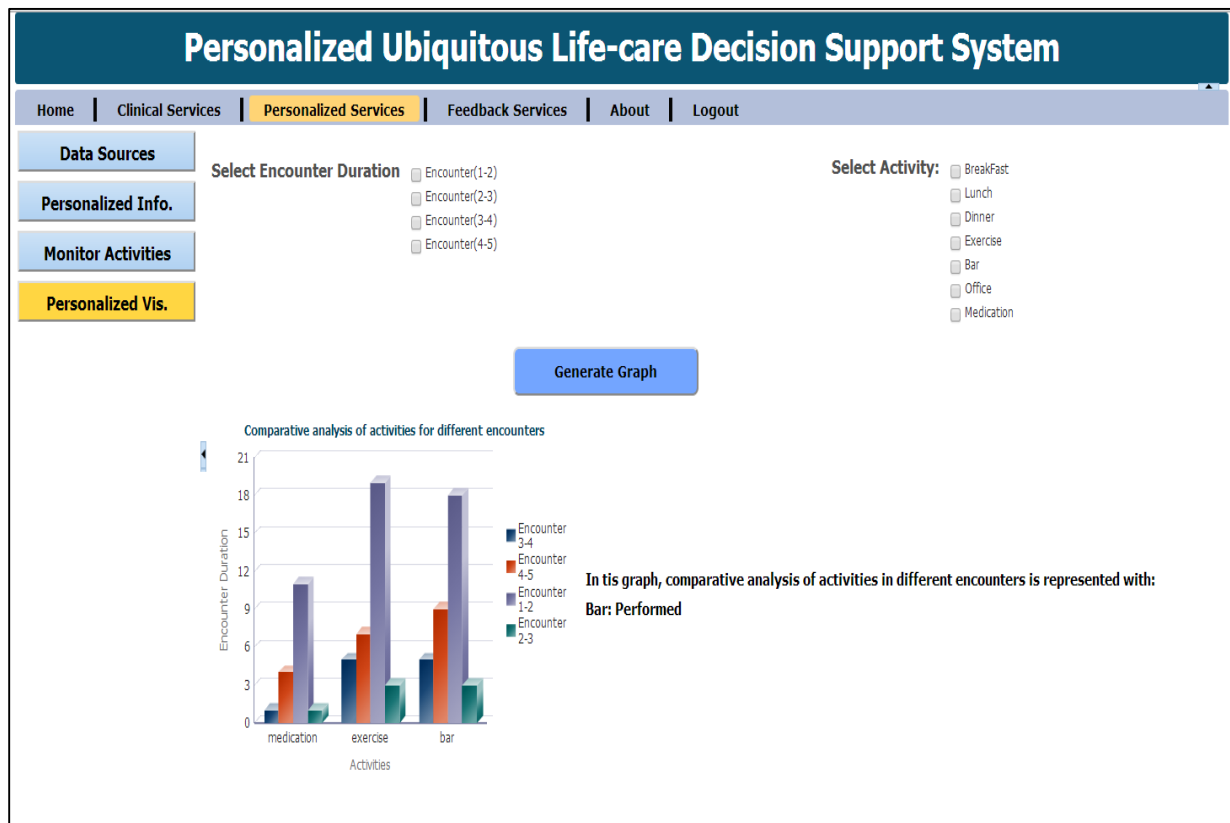
Clinical analytics can help in identifying the abnormal observations and finding out the personalized analytics in specific encounters duration can help in improving the lifestyle and better management of the chronic disease. The daily life activities monitored are also depicted by different colors that shows abnormalities in the different activities. The activities monitored includes: Breakfast, Lunch, Dinner, Exercise, Bar, Office and Medication. Bar activities includes the number of time patient has visited the bar while other activities shows the number of times these are missed by the patient.



The different colors shows abnormalities in activities between different encounters as well as individual abnormalities in performing the activities. The categories for abnormalities in encounter are Default, Near Optimal Life-care Pattern, and Moderate Life-care Pattern, Bad Life-care Pattern, and Improper Life-care pattern. The later categories shows considerable amount of activities not performed accordingly. Therefore, we can see that between encounter and encounter 2, the activities monitored shows improper life-care pattern and hence the blood sugar level was not appropriate throughout.



Visualization of these shows that medication, exercise and bar are activities that are not performed properly by the patient and therefore, encounter 2 shows high FBS value.



7.5 Feedback Services

Evaluation of the system is done by interacting with the user through feedback services. The user can not only provide feedback using the free text service but also provide confidence value on the recommendations provided by the system. Another aspect is the trusted network build on basis of the symptoms and recommendations.

Personalized Ubiquitous Life-care Decision Support System

[Home](#) | [Clinical Services](#) | [Personalized Services](#) | [Feedback Services](#) | [About](#) | [Logout](#)

Provide Your Feedback:

1- Have you checked the overall clinical information monitoring analysis of your Electronic Medical Record(EMR)
☐ Yes ☐ No ☐ To Some Extent

2- Have you checked the overall personalized information monitoring analysis of your personalized activities?
☐ Yes ☐ No ☐ To some extent

3- Are you satisfied with the results provided by the system?
☐ Yes ☐ No ☐ TO some extent

4- Do you think current health analytics mechanism is sufficient to satisfy patient lifecare?
☐ Yes ☐ No ☐ To some extent

5- What improvement you would like to suggest in the system for better analysis of diabetes?

Rate the system

★

★

★

★

★

Submit FeedBack

Chapter 8: Conclusion

The proposed decision support system provides personalized healthcare services by constructing intelligent knowledge base using social, sensory and clinical information. Also, it utilizes the cloud infrastructure to reduce healthcare cost and facilitates interoperability among different heterogeneous healthcare services. Security and privacy is also taken into consideration and is provided by the system ensuring secured sensitive healthcare data exchange. Inferencing the diverse dataset of information is another aspect covered by PULSE-Chronic Disease. The whole communication is carried out using healthcare standards such as HL7, Arden Syntax, and MLM. The system is extensible, flexible, scalable and also provide automation in recommendation generation process.

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