Development of an E-mental Health Infrastructure for Supporting Interoperability and Data Analysis

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Abstract. Digital technology plays an increasingly important role in addressing the challenges faced by health and care services such as rising costs, changing demographics, shortage of healthcare professionals. eHealth is the use of information and communication technologies (ICT) for healthcare systems which helps patients and healthcare providers work together to ensure faster, safer and better care. eHealth strengthen the use of ICT in health development through a range of services or systems including electronic health record, clinical decision support system, health informatics, self-monitoring healthcare devices, personalized medicine. This paper presents an eHealth infrastructure for E-mental health which is under development. The infrastructure is being designed to provide internet based interventions and support for interoperability and data analysis.

Keywords: healthcare systems, internet of things, process mining, machine learning, HL7 FHIR

1 Introduction

Today's vast amount of medical data need to be integrated and accessed intelligently to support better healthcare delivery. Interoperability in healthcare can bring together partners and facilitate knowledge sharing which can potentially create new networks of knowledge. Delivering context relevant clinical information enables decision making through healthcare data analysis. By measuring and monitoring processes digitally, we can compare data more easily. Such insight facilitates streamlined workflows, greater efficiency and improved patient care. Systematic analysis of healthcare data can help to detect patterns so that healthcare providers can optimize their resource allocation and clinicians can conduct treatments to individuals and project better health outcomes. According to WHO a mental health information system should enable managers and service providers to make well-informed decisions that improve the quality of care [7]. To improve the effectiveness and efficiency of mental health services, mental health information systems go through the following essential stages:

– Collection : Data collection from source

- Processing : movement of data from the source
- Analysis : examination and study of the raw data
- Dissemination : communication of the results of the analysis
- Use : utilization of the results of the analysis for service improvement, planning, development and evaluation.

In this paper, we give an overview of an E-mental health infrastructure that facilitates the development of mental health information systems. In many developed countries, majority of their citizens use public healthcare services. To support a variety of healthcare service providers, these healthcare systems often use a large number of software applications. For collecting and processing healthcare data from various sources we require healthcare interoperability. The term 'interoperability' refers to the ability of different information systems to exchange information and understand the semantic of information. Healthcare interoperability is very essential to reduce the processing time that is required for the conversions of healthcare information originated by different healthcare providers and/or systems. It is considered as one of the biggest challenge in today's healthcare systems due to the fact that healthcare systems are inherently complex and there are many players involved in the healthcare industry. There has been a lot of initiatives to address healthcare interoperability over the past decade. HL7 [8] is an international community who is involved in the development of a set of international standards, guidelines and methodologies for sharing healthcare information among healthcare providers. These standards are referred to as HL7 standards. HL7 FHIR (Fast healthcare Interoperability Resources) [6] is the latest standard developed by HL7 for exchanging healthcare information with a main focus on implementation. It provides a number of resource types which are the building blocks for exchanging healthcare data. Any healthcare information that needs to be exchanged among organizations should be specified as FHIR resources. The FHIR standard is suitable to integrate healthcare applications across organizations, medical devices, and also mobile healthcare applications. FHIR resources utilize standard terminologies from ontologies which provide semantic interoperability. Currently we are developing an interoperability healthcare platform based on HL7 FHIR in collaboration with Helse Vest ICT [2], a large IT service provider in Western Norway. The infrastructure development is partly supported by the 'Intromat' project [3].

There is a great need for doing research in health service improvement to provide the best care possible to the patients with limited resources. Research related to health service improvement needs to undertake many complex tasks such as root cause analysis, capture information from previous steps into a simple document and study the variability of a large number of patient population. It is challenging to accomplish these tasks and therefore we require techniques and tool support. For the examination and study of healthcare information we use data mining techniques. Data mining techniques provide deeper insights into patients health by analyzing historical healthcare information including patients diet, appointments, exercise, lab results, vital signs, prescriptions, treatments, allergies, etc. Data mining techniques such as process mining in healthcare brings the opportunity to learn from patients healthcare information including children, women, elderly, patients with co-morbidity and the results can be utilized for optimizing healthcare resources and the improvement of health service delivery.

We need to disseminate the analysis results to a diverse group of people in the healthcare system. Healthcare managers, analysts and clinicians need to visualize healthcare processes across disciplines to investigate the common pathways of patients. Identifying common pathways for patients flow in healthcare systems is complex as we need to deal with a variety of patients group. While analyzing common pathways for patients, different context need to be setup to focus on different group of patients and visualize their careflows. For instance, the manager of the pediatrics department in a hospital would be interested to look at the flow of patients' admission at the children clinics and other departments to make a better planning of resource distribution; a clinician would be interested to investigate the common pathways of patients with mental and behavioral disorders to extract knowledge about concurrent common mental disorders; an analyst may be interested to investigate the efficiency of a new planning strategy. Resources in healthcare may include time, money, facilities, equipment, people and competences. Proper resource planning needs to be carried out in healthcare to ensure that healthcare providers are not overloaded with work, patients are not waiting too long to get services, and the overall cost of healthcare is optimized. In our approach, we disseminate the results of careflow analysis to healthcare professionals for service quality improvement.

2 System architecture

There are a variety of health service providers in a healthcare system and the healthcare data are often siloed away from other data. Data silos is not only the problem in a healthcare setting but different standards are being followed by different health facilities to code diagnosis, lab test results, medical procedures and drugs. Variety of data models of different service providers are making data analysis challenging. To address this issue, it is therefore important to create an infrastructure for ad-hoc exploration of large collections of data. Such an infrastructure needs to be flexible and scalable yet supporting suitable format for decision making. We envision a healthcare information system that provides access to information from various healthcare providers as well as patients personal healthcare devices and/or applications. Availability of information from patients personal healthcare devices can potentially be used to detect complicated problems correctly in their early stage and monitor the effects of treatment. For instance, bipolar disorder can be difficult to diagnose and according to a study published in Psychiatry, around 69 percent of bipolar disorder cases are misdiagnosed [13]. Analyzing patients personal healthcare information can be used to identify periods of mania and depression. Correct identification of depressive and one manic or hypomanic episodes are important factors for the diagnosis of bipolar disorder. However, the integration of personal healthcare devices in the mainstream treatment process will require the use of healthcare standards.

We chose to use HL7 FHIR as it allows us to integrate healthcare information collected from several sources. Although HL7 FHIR provides a suitable way to harmonize healthcare information, it does not provide any sophisticated visualization technique to get an overview of patients health or administrative information. In our approach, we apply process mining techniques for extracting an overall picture of healthcare information from various contextual view and from different level of abstraction and utilize machine learning techniques to constantly monitor patients condition and raise alarms.

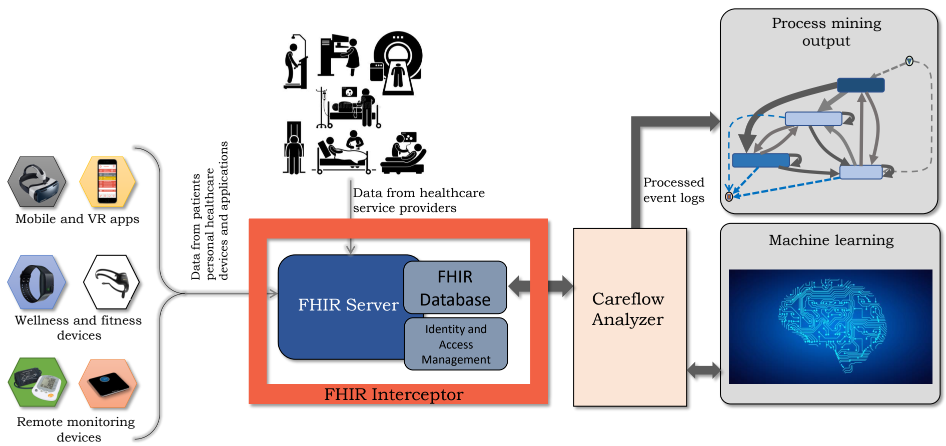

Fig. 1. A system architecture for E-mental health

Figure 1 illustrates an E-mental health system architecture where a FHIR database is used to store the data captured from healthcare service providers as well as patients personal healthcare devices and applications. A careflow analysis tool is used to perform data analysis including process mining and machine learning. The careflow analyzer prepares the event logs by querying the FHIR database. Security and privacy are major concerns for healthcare systems. Different types of users may be involved in the process mining related work. The users must have proper authorization to access patients healthcare information. It might be possible to give partial access to the healthcare information stored in the FHIR database. A FHIR interceptor is incorporated in the system architecture to handle users authorization to access FHIR resources. The interceptor will intercept all the FHIR queries and consults with an identity and access management module and returns data that the user is authorized to access.

We have developed applications to provide digital interventions for some clinical cases such as managing depression, monitoring bipolar patients status, treatment for social anxiety disorder [3]. Currently patients need to sign up to become a part of a clinical study program and they use their BankID for authentication which is a personal electronic ID used to identify and sign online. BankID is a Public Key Infrastructure (PKI) solution offered by Finance Norway.

The solution supports both authentication and signing. Our future plan is to incorporate blockchain technology using hyperledger fabric [5] where the patients would be able to receive mental healthcare services anonymously. Public stigma is a barrier to mental healthcare and many people either do not seek treatment or dropout from mental health treatment. We look forward to a solution where patients identity will be hidden but they will be able to get help from a support group of professionals. The patient will own the data and they will be able to decide if they want to share their records with their therapist. We will study the applicability of blockchain technology in developing E-mental health solutions by exploring the potential of using blockchain technology to incorporate security, privacy and integrity of medical records.

3 Data analysis

Typically, a process model describes the activities needed to be performed within a given process by different actors such as physicians, nurses, and lab technicians. Therefore, mining a process would in general extract a process model representing the activities being performed in a healthcare system. The primary focus of process mining in healthcare is to provide evidence-based process analysis techniques for effective process management [11]. It is used to discover trends and patterns of process executions by analyzing the trace of activities (a.k.a event logs) performed in a system. Due to the multidisciplinary nature of healthcare, the event logs need to be harmonized before they can be processed. Getting the right setup for data preparation is important to get the best understanding out of the data as effectively as possible [12]. In a healthcare setting, the data preparation task is complex due to the involvement of various healthcare systems and variations of data formats. We propose to employ data warehouse techniques to pre-process vast amount of information.

Existing process mining tools or techniques [1, 14, 15] have limited support to provide abstraction from different perspective, and healthcare analysts currently need to perform a lot of manual investigation to find out the pattern of patients treatment flow. Given a large number of patients records, this is not an efficient process as they need to change context from one patient group to another and, need to look into the data for a specific time range. To overcome this limitation, we propose to develop a diagrammatic approach that will allow analyst to specify process mining requirements diagrammatically such as the context and abstraction level.

3.1 Role of ontologies in process mining

Ontologies are often used to standardize terminologies in healthcare. For example, the ICD-10 (International Classification of Diseases) ontology is designed to provide diagnostic codes for classifying diseases, including wide variety of signs, symptoms, abnormal findings, etc. The SNOMED CT [4] ontology provides a comprehensive terminology for clinical health. It has been well accepted

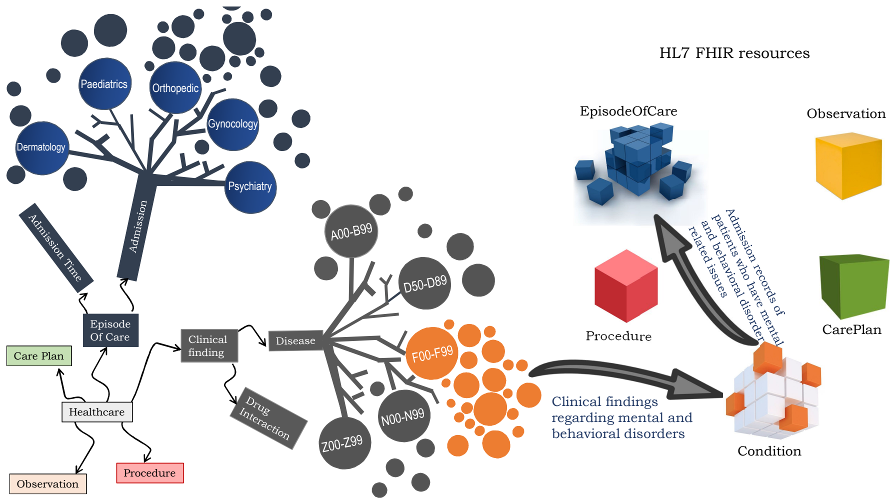

Fig. 2. Use of dimensional model for specifying process mining requirements

by healthcare professionals worldwide and its use has improved the quality of medical health records by providing consistency in using medical terms. Ontologies can be used to define suitable level of abstraction for selecting a particular patient group and for visualizing care-flow from a high level of abstraction. We intend to provide a customizable framework where domain ontologies such as ontologies for care-plans, symptoms can be easily constructed and attached to the data source.

3.2 Dimensional modeling

The concept of dimensional modeling originated from data warehousing and business intelligence (DW/BI) [9]. Dimensional modeling has emerged as the leading architecture for building integrated DW/BI systems. Dimensional models package the data in a format that allows simplicity for displaying understandable information to business users and also supports developing efficient data analytic tools in terms of query performance. We propose to use dimensional modeling for specifying process mining requirements. The dimensional models are used for both filtering and selecting the level of abstraction for visualizing the process mining output. For instance, an analyst may be interested to investigate the admission flow of patients who have issues related with mental and behavioral disorders. He needs to know which other departments the patients also visit. He does not need to know the details about the clinics in the departments where the patients visit. We assume that the department hierarchy of the hospital is used for the 'Admission' dimension. We illustrate the situation in Figure 2 to visualize how the dimensional model and the hierarchical representation of data can be utilized to specify such requirements. The purpose of this dimensional model is to provide an easy to use visualization for its user to investigate careflow from different context. We have used ontological hierarchies to provide hierarchical representation of healthcare information along each dimensional model. In this figure, 'F00-F99' is the ICD-10 code for 'mental and behavioral disorder' diseases. Selecting 'F00-F99' for filtering essentially means to filter based on the sub-diseases under 'F00-F99' which are depicted as small orange circles in the figure. Performing this filter over the FHIR resources extracts the 'condition' FHIR resources where patients condition has been identified as one of the sub-disease code of 'F00-F99'. We use this filtered patients identifications to extract their admission resources. Patients admission resources contain information about patients visit to different clinics. Since we need to display patients admission to the departments, we use departments hierarchical information to manipulate the results displaying department names instead of clinics name. This example illustrates the department hierarchy of the Haukeland University Hospital for the 'Admission' dimension. We use this filtered patients' identifications to extract their admission resources. Patients admission resources contain information about patients visit to different clinics.

4 Conclusion and Future work

The establishment of any large IT infrastructure for healthcare on a regional, national or international level governs by political influences. The Norwegian Center for E-health Research recently published a report [10] on reviewing the focus on machine learning, natural language processing, data mining and process mining methods: their usefulness, use cases, tools and relatedness to Norwegian healthcare. The report emphasized on doing more research in machine learning, data and process mining and natural language processing. Our effort on developing a software infrastructure for E-mental health is aligned with the focus and interest published by the report. Interoperability and healthcare analytics are two major topics in healthcare related research. In this paper, we proposed an IT infrastructure for E-mental health to achieve interoperability and data analysis with cutting-edge technologies.

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