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ORIGINAL ARTICLE

A distributed clinical decision support system architecture

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Abstract This paper proposes an open and distributed clinical decision support system architecture. This technical architecture takes advantage of Electronic Health Record (EHR), data mining techniques, clinical databases, domain expert knowledge bases, available technologies and standards to provide decision-making support for healthcare professionals. The architecture will work extremely well in distributed EHR environments in which each hospital has its own local EHR, and it satisfies the compatibility, interoperability and scalability objectives of an EHR. The system will also have a set of distributed knowledge bases. Each knowledge base will be specialized in a specific domain (i.e., heart disease), and the model achieves cooperation, integration and interoperability between these knowledge bases. Moreover, the model ensures that all knowledge bases are up-to-date by connecting data mining engines to each local knowledge base. These data mining engines continuously mine EHR databases to extract the most recent knowledge, to standardize it and to add it to the knowledge bases. This framework is expected to improve the quality of healthcare, reducing medical errors and guaranteeing the safety of patients by helping clinicians to make correct, accurate, knowledgeable and timely decisions.

1. Introduction

Healthcare faces multiple problems, including high and rising expenditures, inconsistent quality and gaps in care and access. For this reason, healthcare services represent a major portion of government spending in most countries (Canadian Institute for Health Informatics, 2012). Healthcare information technologies, especially EHRs, have been thought to be a possible solution to healthcare problems. EHRs help administrators, physicians, nurses, researchers and healthcare personnel. An EHR provides a complete, integrated and consistent view of patient conditions. However, the volume of data is considerable and is increasing continuously. Healthcare personnel must take all of the patient medical history into consideration; these personnel also need to connect this information together and receive advice from domain experts. This large amount of data cannot benefit physicians without having an automated system. The system can analyze these data, connect it, integrate it with knowledge from a domain expert, and search for a

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needed knowledge – if possible – in other connected systems. This system is a clinical decision support system (CDSS).

CDSSs are computer applications that assist practitioners and healthcare providers in decision making through timely access to electronically stored medical knowledge (Giannopoulou, 2008), to improve the practitioners' medical practice. A CDSS interacts with practitioners and electronic medical record systems to receive the patient data as input and provides reminders, alerts, or recommendations for patient diagnosis, treatment, long-term care planning, and other aspects. A clinical decision support system requires access to healthcare data and knowledge that are stored in data and knowledge bases. In this paper, we attempted to build a complete architecture for this system. The proposed model will take an order and an initial diagnosis from healthcare personnel and will provide a decision support in an understandable form based on existing knowledge. It will integrate off-line standardized knowledge bases from domain experts and Clinical Practice Guidelines (CPG) knowledge with online knowledge that is extracted continuously from EHR databases and provides applicable decision support. This paper is organized as follows. Section 2 discusses related work. Section 3 explains the research problem. In section 4, we define a CDSS. The proposed framework for a CDSS is discussed in section 5. The conclusion is shown in section 6.

2. Related studies

In this section, we go through some background about essential principal aspects of health informatics that are related to CDSSs. EHR (Yina, 2010), EHR standards, data mining and artificial intelligence, service oriented architecture and knowledge representation are strongly related to CDSSs.

2.1. EHR standards

Many organizations provide EHR standards that standardize structuring, implementation, sharing, integration and interoperability in an EHR environment. Some of the standards are ISO (International Organization for Standardization, 2012), CEN (The European Committee for Standardization, 2012), CFR (The World Health Organization, 2012), ASTM (ASTM International, 2012), HL7 (The Health Level Seven, 2012), NEMA (National Electrical Manufacturers Association (NEMA), 2012), and ONCHIT (US Department of Health and Human and Services, 2012). In addition, coding systems are critical to build a shared EHR because the new environment connects each heterogeneous system with different terminologies. Some organizations that provide these standards are Regenstrief (The Regenstrief Institute, 2012), AMA (The American Medical Association, 2012), IHTSDO (International Health Terminology Standards Development Organization, 2012), CMS (US Department of Health & Human and Services, 2012), and WHO (The World Health Organization, 2012). These organizations provide standards for encoding healthcare data and knowledge.

2.2. Data mining and artificial intelligence (AI)

Applying data mining and AI techniques on EHR data provides many opportunities for improving delivery, efficiency, and effectiveness of health care (Ramakrishnan et al., 2010; Giannopoulou, 2008), such as operations management, preventive healthcare, chronic disease treatment and prevention, association analysis, evidence-based treatment, and population tracking. If CDSS depends only on the Knowledge Base (KB) that is derived from a knowledge expert, then it will be inactive and not applicable. There are two other sources for knowledge. The first source is CPG, which publishes free text guidelines. These guidelines are created by using many methods, such as Systematic Reviews and Meta-analysis. The modeling CPG knowledge is formulated in rules that use many methodologies (Peleg et al., 2003). The other source is the application of data mining techniques on EHR data. EHRs contain a very large and historical dataset that changes continuously and contains useful hidden knowledge. As a result, data mining and AI services should be embedded into the active CDSS to continuously update its knowledge base by the most recent patterns.

2.3. Knowledge representations in the medical domain

Because there are many sources and uses for medical knowledge, many methodologies and standards for representing medical and healthcare knowledge are integrated. Clinical workflows (clinical guidelines) are used to represent human-based medical knowledge through rule-based or flow-based guideline techniques. Furthermore, mined knowledge can be automatically extracted from EHR databases through data mining and AI techniques, to be incorporated into human-generated knowledge that enhances their decision-making processes.

Both types of knowledge can be represented as logical conditions, rules (Kuo and Fuh, 2011), graphs/networks, or structural representations (Kong et al., 2008). Predictive Model Markup Language (PMML) (Data Management Group (DMG), 2012) and GLIF (Guideline Interchange Format (GLIF), 2012) are examples of knowledge representation languages that are used to acquire and integrate knowledge. Additionally, there are many tools for knowledge acquisition and representation, such as Unified Medical Language System (UMLS) Bodenreider, 2004, Protégé (Protégé Official Web Site, 2010; Chen et al., 2011), GLARE (Terenziani et al., 2004), PROforma (PROforma, 2010) and ASBRU (Open clinical, 2010).

2.4. Service oriented architecture (SOA)

A SOA has been widely adopted to solve the interoperability of the involved heterogeneous distributed EHR systems (Hahn et al., 2010; Maciel and David, 2007). This architecture plays a key role in the integration of heterogeneous systems by means of services that represent different system functionality, independent of the underlying platforms or programing languages, and interacts via message exchanges. *Web services* also play a critical role in systems' interoperability. Web services technology is defined as a systematic and extensible framework for application-to-application interactions that is built on top of existing web protocols. These protocols are based on XML (World Wide Web Consortium, 2012) and include: Web Services Description Language (WSDL) to describe the service interfaces, Simple Object Access Protocol (SOAP) for communication between web services and client applications, and