Upgrading legacy EHR systems to Smart EHR systems

Ane Murua[1,2], Eduardo Carrasco[1,2], Agustin Agirre[3], Jose Maria Susperregi[3] & Jesús Gómez[3]

[1] Vicomtech-IK4, Donostia – San Sebastián, Spain
{amurua,ecarrasco}@vicomtech.org
[2] Biodonostia Health Research Institute, San Sebastian, Spain
[3] La Asunción Clinic, Tolosa, Spain
{aagirre,jsusperregi,jesusgm}@clinicadelaasuncion.com

Abstract. Electronic Health Record (EHR) systems are a key element of the clinical practice in most hospitals and healthcare organizations. Although traditionally its role has been focused mainly as a patient health data storage and communication tool, thanks to the recent technical advancements, a wide range of new promising possibilities are arising. This paper discusses a set of different technologies that can be added to a legacy EHR system in order to provide new functionalities and upgrade it into a Smart EHR system.

Keywords: Electronic Health Records · Personal Health Records · Knowledge Engineering · Rule-based Systems · Business Process Management · Natural Language Processing · Intelligent Agents

1 Introduction

The management of large amount of patient information in medical practice has made the medical record the cornerstone of clinical communication and documentation [1]. This patient information was stored in the form of paper based medical record entirely until early 1960s when the idea of electronic medical record was introduced [2] and progressively extended since then.

The implementation and adoption of EHR systems throughout the world differ in developing and developed countries [3]. The developing countries are starting to implement EHR systems as supporters of paper-based health records [4], while many developed countries have nationwide policies in order to foster EHR adoption. In several countries (e.g. New Zealand, Sweden, Norway, Netherlands, United Kingdom, Australia or the United States), the percentage of primary care physicians using electronic medical records is almost 100% [5].

Literature shows that EHR systems provide relevant benefits for clinical outcomes (e.g., improved quality, reduced medical errors), organizational outcomes (e.g., financial and operational benefits), and societal outcomes (e.g., improved ability to conduct research, improved population health, reduced costs). Similarly, several important drawbacks can be identified as well such as the high upfront acquisition and maintenance costs, disruptions to clinical workflows, losses in productivity in the learning

adfa, p. 1, 2011.

stages [6]. Nevertheless, it is agreed that significant benefits are brought to patients and society when EHR systems are used in an appropriate way.

2 Next-generation EHR systems

Due to the relevance of EHR systems in our society, intense research and development has been conducted and new definitions are starting to emerge. In this sense, according to [7] an Electronic Health Record (EHR) system includes: (1) longitudinal collection of electronic health information for and about persons, where health information is defined as information pertaining to the health of an individual or health care provided to an individual; (2) immediate electronic access to person- and population-level information by authorized, and only authorized, users; (3) provision of knowledge and decision-support that enhance the quality, safety, and efficiency of patient care; and (4) support of efficient processes for health care delivery.

New information and communication technologies have the potential to fully meet and extend the aforementioned goals, but, in order to do so, several relevant technical challenges have to be addressed.

First, the data contained in the EHRs has to be further structured and codified using standardized terminologies. Experts agree on that 80% of the data in the healthcare sector is unstructured, and hence no further exploited [8].

Next, patient health data is expected to continue growing exponentially in the coming years and a great part of all these data will be physically scattered beyond the limits of the healthcare organizations. The management of all this information and the access and privacy issues involved raises new challenges for the EHR systems [9].

Third, available healthcare data has to be transformed into reusable knowledge, and this knowledge will be confronted with stablished clinical guidelines in order to discover the best practices that lead to the best decision support given to the medical practitioners [10].

Finally, medical workflows have to be automated in the EHR systems as much as possible in order to increase the efficiency of the health care delivery [11].

Relevant EHR systems have been developed in the last years that are aligned with these challenges such as Kaiser Permanente [12] or openEHR [13], but still progress has to be carried out in order to meet them at their full extent.

3 Methods for upgrading legacy EHR systems

In this section, several technologies that can be integrated into legacy EHR systems in order to upgrade them into Smart EHR systems are described.

3.1 Data curation

The first milestone for upgrading a legacy EHR system is to improve the quality of health data contained in it, to foster its reuse, to add more value to the data and to add complementary sources of data.

Natural Language Processing techniques

As stated above in this paper, 80% of the data in the healthcare sector is in unstructured formats which include machine-written, handwritten information and audio dictations among others. In these formats, relevant health information is "locked" since they were intended only for human reading and interpretation.

Extracting key data elements from unstructured medical records into structured computable data elements is an essential step for EHR information reuse. Natural Language Processing techniques are a straightforward tool to help automating this task. Numerous researchers and academic organizations have been exploring over the last decade the potential of natural language processing for risk stratification, population health management, and decision support. A recent example of a machine learning NLP in the healthcare industry is IBM Watson, which has been focused in clinical decision support for precision medicine and cancer care [14][15].

In order to facilitate the computer-assisted extraction and understanding of the most relevant terms of the EHR records, available terminologies such as SNOMED CT or ICD 10 are used. UMLS [16] is remarkable as well, since it integrates and relates most relevant biomedical vocabularies available so far.

Standardized Data Models.

During the last decade different EHR standards had been developed for EHR modelling. The most extended ones are (i) HL7, (ii) ISO EN13606 and (iii) openEHR.

Although each standard brings a particular differential feature compared to others, all agree on a dual model structure, consisting on a reference model (RM) and an Archetype Model (AM).

The RM supports information within a structure, based on well-established concepts independent from knowledge. It represents the characteristics of the general components and their organization. AM defines and models concepts of clinical knowledge following the structure and constraints imposed by the RM.

The combination of both models in a single frame provides of structure and semantic interpretation to the content stored in the EHR [17].

Integration of distributed patient data

According to an American study carried out by the "California HealthCare Foundation" in 2013 [18], 7 out of 10 adult Americans regularly measure at least one of their health status related indicators, such as their weight, diet or activity level.

A gradual transformation is occurring, causing the individual -who used to be a passive "element", merely an information generator -, to become a subject capable of analyzing its own data and even able to start acting according to the insights gained from its self-tracking [19].

Patient's own health and lifestyle data is meaningful for health organizations and should be integrated with the EHR in the form of a Personal Health Record (PHR) [20].

Besides the data annotated by the patient himself, PHR could contain data from other sources, such as: data gathered from sensors or other wearable computing devices, data acquired through mainstream smartphone applications' APIs, activity in social networks or current communication channels.

3.2 Rule-based systems

In a rule-based system the key idea is to separate knowledge and represent it as facts and rules, that is, as conditional sentences relating statements of facts with one another [21]. A rule-engine (e.g. Drools, CLIPS, OpenRules, JESS) provides an alternative computational model which can take rules (declared as a group of "if-then" statements) and execute them over data.

When the conditions stated in a rule are met ("if"), the rule is evaluated ("then") and our facts are updated accordingly.

The information contained on the EHR and PHR can be processed in a rule-based system to provide, according to [22], patient-specific, situation-specific alerts, reminders, or other recommendations for direct action; and to organize and present information in a way that facilitates problem solving and decision making using appropriate visual analytics technics.

3.3 Business Process Management

Business Process Management (BPM) is a methodology which describes the whole life cycle of how to discover, formalize, execute, and monitor our business processes. Business process models are modelled using predefined notations such as BPMNv2 [23], defined by the OMG group. These models have a graphical diagram showing the exact sequence of the activities that are going to be executed and include activities performed by both people and computers.

The most common uses of the BPM methodology in the healthcare field are:

- Computer-interpretable clinical guideline modelling.
- Health center's own (clinical, management, supply-chain, …) workflow orchestration.
- Implementing structured multidisciplinary care plans that detail essential steps in the care of patients with a specific clinical problem (care pathways)

Business processes can be used as a standalone tool or combined with rule-based systems. The most common patterns of rule and process integration are: (1) Including in a process a specific type of task called a Business Rule Task where a Rule Engine is called with some data to get some results; (2) Using rules to start processes to deal with different scenarios difficult to perform by just chaining rules; and (3) Inserting our Process Instances as facts, among some other facts, in a Rule Engine.

3.4 Intelligent Agents

Intelligent Agents are typically described as autonomous artificial entities that sense the world on a continuous basis and act (proactively or reactively) on it in order to achieve specific tasks, such as event detection, maintenance of a domain knowledge model, learning from their observations to improve performance [24].

These agents run in Multi-Agent Systems MAS which are integrated with the information systems in many different sectors. The integration of MAS with the EHR could lead into more advanced scenarios, i.e. applying intelligent agents in the healthcare domain with a wide range of applications, such as:

- *Data-management systems.* The focus is on the efficient retrieval and processing of scattered medical data, for example combining patients' data in the EHR with other sources such as most recent evidences available for treatment.
- *Decision Support Systems (DSSs).* DSSs provide patient-specific recommendations based on previous healthcare processes or knowledge-based models for example for diagnosis or treatment selection.
- *Planning.* Systems centered on the coordination and scheduling of human and material resources, for example when executing a standardized clinical guideline.
- *Simulation.* Agents can be used to make rule-based simulations of the behavior of complex challenges, such as to evaluate the impact of particular treatment taking into account the evolution of a disease.
- *Monitoring and alarms.* The goal is to continuously monitor the current state of a patient and, taking into account the evolution and the general context, warn the patient (or a supervisor) about problematic future situations.

4 Conclusions

EHR systems bring significant benefits to patients and society as they contribute, amongst others, to share medical information, to reduce medical errors, to improve coordination of care and health care quality and to lower national health care costs.

This work describes a set of methods focused on upgrading legacy EHR systems. This is a common scenario for EHR system development organizations who want to benefit from state-of-the-art technologies in order to explore new horizons.

The methods addressed in this paper focus on improving the quality of the health data in the EHR, its exploitation and computer reuse, the extraction of medical knowledge from health data, the promotion of computer-aided decision support and the automatization of clinical processes in order to promote efficiency in the healthcare provision. In particular, the technical topics addressed are i) data curation, ii) medical rules management, iii) business process modeling and iv) intelligent agents. The integration of these technologies in the EHR systems will pave the way to a new generation of Smart EHR systems.

Smart EHR systems will bring new appealing scenarios to the healthcare organizations, such as i) empowerment of both patients and health professionals, ii) reuse of health information in order to discovery of new medical knowledge, iii) promote the development of Clinical Decision Support Systems to enhance the quality of the healthcare, iv) increase the sustainability and security by means of the automatization of clinical tasks and v) advance to a Real-world evidence based medicine.

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