Ontological Model for CDSS in Knee Injury Management

Kanitha Phalakornkule, Josette F. Jones, and John T. Finnell

School of Informatics and Computing Indiana University- Indianapolis, USA
{kpa,jofjones,jfinnell}@iupui.edu

Abstract. Due to the increased adoption of Electronic Health Records (EHR) and its integrated clinical decision support (CDS) tools, health information technology (HIT) is a key influence in Medicine. The main challenges in healthcare are to integrate the information across care units and to increase the quality of continuity of patient care. There are three types of knowledge sources in medicine: (1) Evidence Based Practice (EBP), (2) Practice Based Evidence, and (3) Medical Textbooks. Information in these sources is presented and organized in different formats. Ontology may allow us to integrate knowledge discovered from two separate data sources without platform restrictions. The knowledge can be reusable and sharable without the need of technology. Further, this paper also combines the strengths from both EBP and PBE on knee treatment. The hybrid knowledge model will derived from real practices while integrating existing external knowledge discovered and reported in published literatures.

1 Introduction

Since the early 1990s, health information technology (HIT) has played an important role in the improving and continuity of health care delivery globally. One of the main influences comes through the introduction of Electronic Health Record Systems (EHRs) facilitating continuity of care throughout patient's lifespan, and across regional, national, and global healthcare systems. Clinical Decision Support (CDS) Systems play an important key in EHRs by computing and analyzing stored EHR data. CDS systems (CDSS) facilitate decision making at the point of care by advising or alerting clinicians with analyzed information that is in its knowledge model. Based on its knowledge model, CDSS can influence how a clinician makes their decision at at the point of care. Moreover, CDSS can assist clinicians in advising the best evidence or warning of potential risks which the clinicians have not encountered before. Therefore, the knowledge model in the CDSS is a critical key to its performance. The efficiency and accuracy of the knowledge model remain to be fully understood, which prevents CDS in EHR to be fully realized.

There are two types of dynamic knowledge sources for CDSS: (1) Evidence Based Practice (EBP) and (2) Practice Based Evidence. Knowledge from the Evidence Based Practice or EBP collects and utilizes the best available academic research evidences as data, while Practice-Base knowledge is derived from the learning through clinicians' own experiences in the day-to-day profession (Barkman and Mellor-Clark

C. Stephanidis and M. Antona (Eds.): UAHCI/HCII 2013, Part III, LNCS 8011, pp. 526–535, 2013.

2003). EBP has been in Medicine for decades and is more commonly used in CDSS so it tends to bring many promises. However, EBP should not be used by itself without requiring additional new information about each different patient, each singular clinician and hence each dissimilar practice, since its knowledge is based on aggregated data from a specific group of population of specific interest in a controlled environment which does not likely exist in a real practice. Additionally, many of compound variables in research studies are not published in articles; therefore, the influences of these variables are unknown and are not taken into account when the CDSS's knowledge model based on EBP is applied in the real practice. This is why the efficiency of EBP has been questionable.(Green 2006 & 2008)

On the other end, Practice-Base Evidence (PBE) only utilizes clinical expertise and gathers data from the evidence during practices. PBE mainly collects evidence from routine practices with similar, if not the same, aims and outcomes in uncontrolled environment. Outcomes resulted from a practice-based study have higher external validity because they are based on routine practice. With a PBE approach, the experiences gained in individual practices will be reviewed and learned at the point-of-care. PBE is a more patient-specific approach than EBP because the compound factors in its knowledge model are the same as in the practice. Nevertheless, while PBE approach seems to be a great model to follow, PBE implementation requires large amount of data in order to build a knowledge model. It needs to be able to share its finding and integrate new knowledge to its knowledge base across multiple practices.

Opportunistically, with current EHRs and other technologies, the development of a knowledge network is possible and can be deployed and dispersed rapidly within healthcare organizations. Even though knowledge representation is independent from platform and database systems, the structure of knowledge representation could be based on individual practice's workflow and organization structure in order to be more meaningful and suitable for individual practice (Dang, Hedayati et al. 2008). Ontological concepts and a knowledge editor such as Protégé by Stanford University are well-known tools used in semantic network representing and integrating knowledge models. Using an ontologic approach will allow us to integrate and re-use knowledge discovered from multiple separate data sources without platform restrictions. The hybrid knowledge model will be derived from a real practice setting while integrating existing external knowledge discovered and reported in published literature. This will enhance the performance of the CDS to be patient-specific while being aware of any unknown knowledge and adaptive with high external validation. The innovative focus of this study is to bring both EBP and PBE approaches, along with an ontological knowledge model to CDS's functionality. As of now, there have been no studies published explaining the extraction and value of both EBP and PBE from existing clinical practice data using in CDS, while many studies have demonstrated how to build evidence-based practice (EBP) and its value to clinical practice.

2 Background

In information science, an ontology knowledge framework is known for representing a hierarchical-structure knowledge model that consists of classes, properties or slots, relationships between classes and individuals (or instances) (Gruber 2009) due to its ability to cluster many transaction-level concepts into a domain level (T. Mabotuwana 2009). It's structure is in hierarchical or in topology format similar to a human making a decision (Milgrom 2010). Many studies in medicine implemented an ontologic approach in order to measure qualitative outcomes. Another main benefit of the ontologic framework is that it allows the domain knowledge to be independent from technology. In other words, it can be run on multiple platforms with different capabilities (Farion, Michalowski et al. 2009). An ontology knowledge model allows a separation between logic knowledge and software design. It represents a set of concepts and the relationships among them in a hierarchical format. This format can be referenced in the reasoning rules in machine learning. Therefore, when the knowledge is changed, only the reasoning is changed without any changes to the software system. Because of these characteristics, an ontologic approach is beneficial for data sharing in EHRs. It isolates medical knowledge from technology. It allows patient's information to be exchanged across health institutions regardless of the EHRs' technology or operation.

One of the well-known uses of ontology in healthcare is terminology server such as UMLS (Unified Medical Language System), SNOMED and LOINC. These servers are well-structured systems in order to offer standardized communication, documentation and classification of health/medical vocabularies (Cole 2004). However, even these terminology systems are all based on a standard structured framework; there are still inconsistencies and incompatibilities among their concepts (B. Bolbel 2006). The terminology structure in UMLS was used as a starting ground for the medical ontology construction. In order to connect the ontologic concepts with the UMLS terms, a special class of UMLS synonyms was built inside the ontology that is linked to the original guideline term through a "UMLS synonym" property. This ontology was used to build structure for automated systems to provide classification within clinical notes. Using this ontology, existing terminology domains can be shared and integrated into existing definitions and terminologies across healthcare level (D. Pappa 2006). It is a key prerequisite for sematic interoperability, especially in the context of knowledge representative and terminologies. (Blobal 2006 & 2007).

An important distinction: medical ontologies differ from terminology ontology frameworks. (Peleg 2008) While the ontology for terminology servers are based on static structures used for knowledge reference and its databases are categorized based on its linguistic concepts, the medical ontology combines all of the relevant concepts. These concepts are related to the diagnostics, treatment, clinical procedures, patient data and outcome prediction (Jovic, Prcela et al. 2007). The ontology in medicine/patient-care environment has to consider changes and temporal factors, especially when it is applied to EHRs. This is because EHRs are patient-center, longitudinal, comprehensive and prospective (S Garde 2007). The existing ontology models also have to be reusable and adaptable to new changes easily. Moreover, there are several stakeholders in medicine. In the same domain, the ontology can be organized in different ways based upon its purpose of design. Consequently, the ontology in medicine can be more complex to design and to share. In some other papers, ontology could be used as a new implementation for a knowledge framework for connecting systems together. Since medicine is a complex system, all studies have to focus on a niche knowledge domain. In order to link or apply these knowledge frameworks to a larger framework, an ontology has to be designed to connect their common interests.

The further use of ontology in EHRs is a framework for clinical decision support functions (CDS). (Sim 2001) The additional requirement for CDS requires statistical methodologies to run reasoning rule-base utilities (Montani, Bellazzi et al.). However, there have not been many studies on the application of CDS in EHR based on individual practices. Nevertheless, the content of patient-centric CDSS implementation can be applicable. This is an important requirement for CDS in EHRs due to the Meaningful Use (http://himssclinicaldecisionsupportwiki.pbworks.com).

In summary, the modern EHRs require a framework to support their enhanced functionalities (S. Mersmann 2004). When the demand of using EHRs expands from local to multiple institutions, a standard framework is in need. Ontology can bring many benefits in the knowledge sharing and can make its knowledge assumptions explicated and independent from operational systems. Ontology can increase EHR's functionalities in standardizing medical terms, knowledge sharing, and support for automatic reasoning using in decision support systems(3). Equally the Era of Patient Safety Implications for Nursing Informatics Curricula paper (J. Effken 2002) concluded that Ontology plays a main role in CDSS, integration and standard for patient safety in clinical environment.

3 Methodology

The implementation of this study consists of two main steps: (1) Developing Ontological Knowledge Framework based on Practice-Based Evidence, and (2) Integrating Evidence-Based Information to the Knowledge Model

1. Developing Ontological Knowledge Framework based on Practice-Based Evidence

The first stage of the study is to capture existing knowledge, then transform it to an Ontological knowledge framework. In this study, our current knowledge is derived from experts and patient-record in a EHR system. The data in EHR systems is recorded in a relational database (RD) formats. RD is mainly utilized for storing and querying high volumes of data, but cannot represent the knowledge behind its database structure. On the other hand, an ontology presents the structure of knowledge in a specific domain, but lack of ability to store and query data. The ontology portion has the universal flexibility to be shared and reused regardless of database systems.

1a) Represent Knowledge with Predicate.

In this paper, the knowledge was not imported directly from EHR system, but it was abstracted through human interpretation and a guideline from domain experts. Based on the study by Jones (2011), the knowledge structural model for patient care is initiated by a high level abstraction of a "healthcare event". The concepts of healthcare events are structured in triplets of subject -> predicate -> object and based on the following description logic premise as shown in Figure (1).

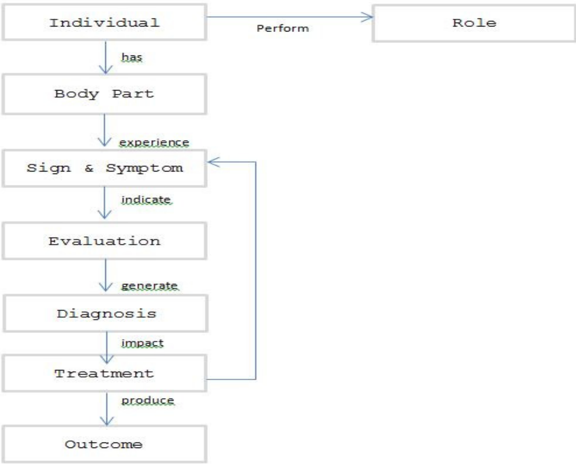

Fig. 1. Health Event Diagram

In this paper, the healthcare events are structured as:

An entity -> has role as -> a patient
The patient -> experiences-> Knee injury
Knee injury -> is evaluated by -> Knee exam
Knee exam-> generates result -> ACL tear
ACL tear -> requires -> ACL reconstruction surgery
ACL reconstruction surgery -> needs -> post-op rehab
Post-op physical rehab -> has an impact on-> Range of Motion
Range of Motion -> effects -> Return to Activity

Now, the main concepts of the domain are captured. These will be used to represent main classes in the ontologic model. The sub concepts will represent choices of their parent concepts. For example, the body part composes of left knee and right knee, while the class "ACL reconstruction surgery" has subclasses based on location of graft (Ipsilateral VS Contralateral).

1b). Implement Ontological Framework in Protégé

Protégé 4.1 (OWL) by Stanford University is used as an ontological editor in this study. There are 9 main classes derived from practiced based evidences as mentioned above.

Class1: Entity

Since this study will merge knowledge from both real practices and publications, the entity class will have two main sub classes: Article and Human.

Class2: Role

There are three categories of the Role class: Patient, Clinician and Study. In the future, the set of roles should be expanded to cover more relationship with patients such as family.

Class3: Body Part

The study treats left knee and right knee as individual class instead of two subclasses of knee class. The knee class is designed as knee anatomy of bone, ligament and soft tissue as shown in Figure 2.

Class4: History

The history class represents history and chief of complaint in EHR. This information is based on patient's own knowledge and history (Figure 3)

Class5: Sign and Symptoms

The sign and symptom class represents physical observation at the current time by clinical staff (Figure 4).

Class5: Evaluation

The Evaluation class includes results from any lab tests, subjective and objective scores (Figure 5).

Class6: Diagnosis

The Diagnosis class represents the summary of patient's information binding to clinician's knowledge. Then the clinician will make a conclusion what disease or health issue the patient is facing (Figure 6).

Class8: Treatment

The treatment class shows the treatment that the patient is received based on the diagnosis. Here, two main subclasses of the treatment plans are surgical and non-surgical treatment (Figure 7).

Class9: Outcome

The concept of Outcome class is to find a set of variables validating if the patient has a good or bad outcome from the treatment.

In addition to the 'heath-event' classes, two new classes are added on the knowledge model: Categories and Sports. The categories class is used to binding information from EBP to PBE. It is not uncommon to find a result reported in articles as qualitative outcomes rather than quantitative outcomes.

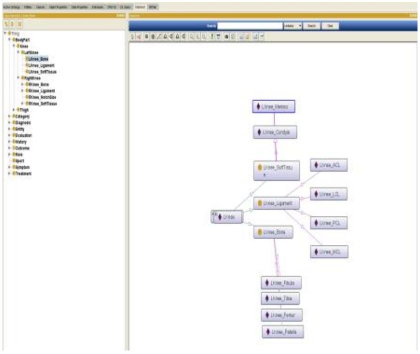

Fig. 2. Body Part (Knee) Class

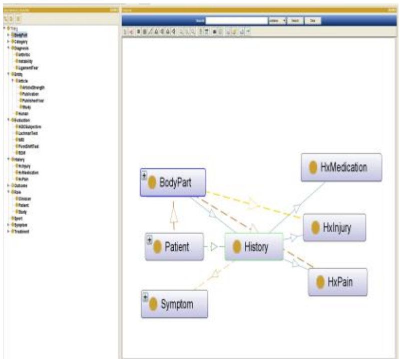

Fig. 3. History Class

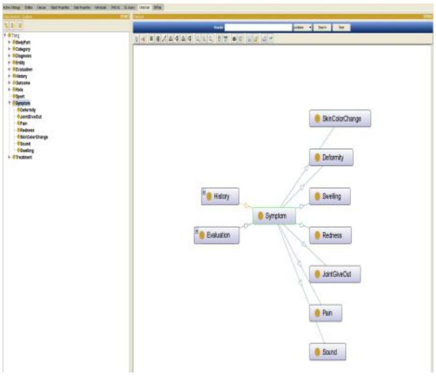

Fig. 4. Sign and Symptom Class

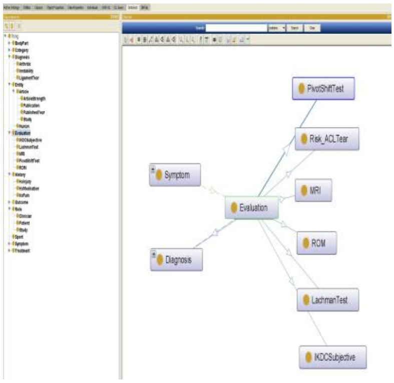

Fig. 5. Evaluation Class

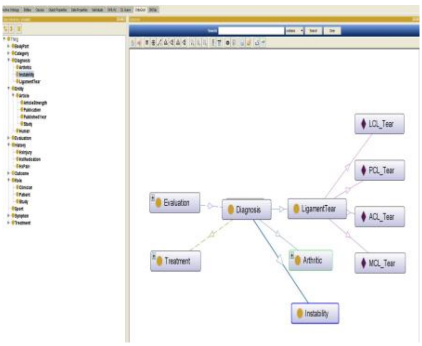

Fig. 6. Diagnosis Class

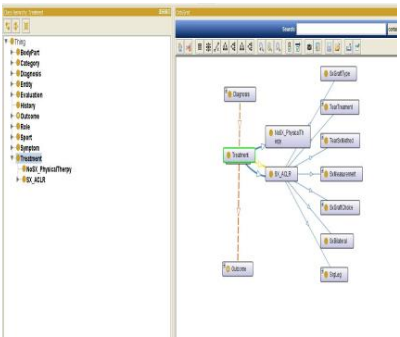

Fig. 7. Treatment Class

4 Integrating Evidence-Based Information to the Knowledge Model

4.1 Measuring Quality of Publications

The challenge in using data from publications are (1) Validating the reported outcomes (2) Merging contradicted outcomes. These two issues could be deflated by comparing the quality of publications. The quality of studies will be evaluated for strength of evidence, validity and reliability. The strength of evidence well be graded 10 levels as listed (Cercone 2011).

- 1A Systematic Review of Randomized Controlled Trials
- 1B RCTs with Narrow Confidence Interval
- 1C All or None Case Series
- 2A Systematic Review Cohort Studies
- 2B Cohort Study/Low Quality Studies
- 2C Outcomes Research
- 3ASystematic Review of Case-Controlled Studies
- 3B Case-Controlled Study
- 4 Case Series, Poor Cohort Case Controlled Studies
- 5 Expert Opinion

The studies will be evaluated for validity and reliability through a Cumulating Evidence Score weighted by the quality of the study (Miller 2009). As a result, the stronger methodological quality and better design research will have higher scores than weaker ones. A database will then be designed in order to record the researches along with its rank into machine-interpretable formats suitable of CDS.

4.2 Developing a Formula for Weighting Publication's Outcomes

The detail in this step is omitted from this paper. The aim is to develop a methodology using Bayesian Network (BN) to calculate the most suitable publications for each individual patient. BN is an appropriate tool for Ontology due to its probabilistic ability and directed acyclic graph (DAG). (Bucci 2011) Then, BN's probabilistic model will be used as a rule in Protégé.

4.3 Implement Rules Representing Knowledge from Evidence-Based

In this step, Rules will be added to the knowledge model. Specific knowledge can be imbedded in the model through rules. This approach will allow the model to be flexible and modify existing knowledge without changing the knowledge structure. For example, one of the rules in this study represented as (Figure 9)

Symptome(?s), signJoinGiveout(?s, "positive") -> RecommendedTest(?s, "LachmanTest")

This is interpreted as

"Any patient having a symptom of join give out, the Lachman test will be recommended for diaganosis".

In the future, if the practice decides to add more tests for the patient, a new rule will be added without changing the knowledge structure.

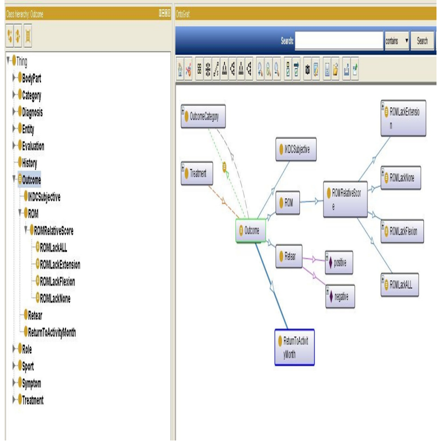

Fig. 8. Outcome Class

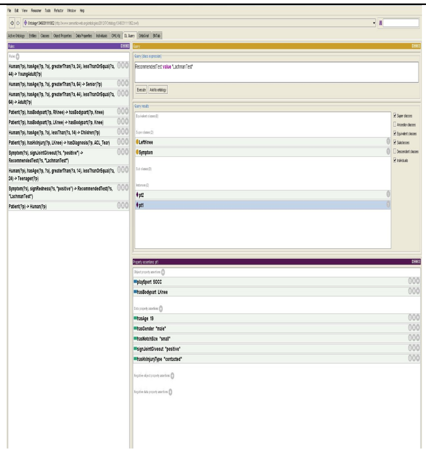

Fig. 9. Rules in Protégé

5 Conclusion

The paper illustrates how we can capture and synthesize different types of knowledge resources that complement each other. The key tasks for the study presented are (1) design the knowledge model and (2) defy a formula for merging information in publications. Designing a knowledge model is intricate because we have future use and reuse more than just to represent current knowledge. There are many ways to model knowledge, but there are only few that can be applied for a specific use. Binding PBE and EBP knowledge together offers more accurate and patient-focus support in clinical decision system. This will allow us to enhance the benefit from EHR systems and improve care.

References

1. Blobal, B.: Educational Challenge of Health Information Systems's Interoperability. Methods Inf. Med. 46, 52–56 (2007)
2. Bucci, G., Sandrucci, V., Vicario, E.: Ontologies and Bayesian Networks in Medical Diagnosis. In: HICSS 2011, Proceedings of the 2011 44th Hawaii International Conference on System Sciences, pp. 1–8 (2011), doi:10.1109/HICSS.2011.333
3. Cole, C.: Using a Terminology Server and Consumer Search Phrases to Help Patients Find Physicians with Particular Expertis. MedInfo (2004)

4. Dang, J., Hedayati, A., Hampel, K., Toklu, C.: An ontological knowledge framework for adaptive medical workflow. Journal of Biomedical Informatics 41(5), 829–836 (2008), doi:10.1016/j.jbi.2008.05.012
5. Green, L.: Public Health Asks Of Systems Science: To Advance Our Evidence-Based Practice, Can You Help Us Get More Practice-Based Evidence? American Journal of Public Health 96(3), 406–413 (2006)
6. Green, L.: Making Research Relevant: if it is an evidence-based practice, where's the practice-based evidence? Practice Advance Access (25), 20–24 (2008)
7. Jones, J., Phalakornkule, K., Fitzpatrick, T., Iyer, S., Ombac, C.Z.: Developing Protégé to Structure Medical Report. In: Stephanidis, C. (ed.) Universal Access in HCI, Part IV, HCII 2011. LNCS, vol. 6768, pp. 356–365. Springer, Heidelberg (2011)
8. Effken, J., Carty, B.: The Era of Patient Safety: Implications for Nursing Informatics Curricula. J. Am. Med. Inform. Assoc. (2002)
9. Milgrom, L.: Toward a Topological Description of the Therapeutic Process. The Journal of Alternative and Complementary Medicine 16(12), 1329–1341 (2010)
10. Montani, S., Bellazzi, R., Riva, A., Larizza, C., Portinale, L., Stefanclli, M.: Artificial Intelligence Techniques for Diabetes Managements: the T-IDDM Project
11. Peleg, M., Denekamp, K.S.,, Y.: Mapping computerized clinical guidelines to electronic medical records: knowledge-data ontological mapper (KDOM). J. Biomed. Inform. 41(1), 180–201 (2008)
12. Sim, I., Gorman, P., Greenes, R., Haynes, B., Kaplan, B., Lehman, H., Tang, P.: Clinical Decision Support Systems for the Practice of Evidence-based Medicine. Journal of the American Medical Informatics Association 8(6), 527–534 (2001)