DISCOVERY OF HIGH QUALITY KNOWLEDGE FOR CLINICAL DECISION SUPPORT SYSTEM BY APPLYING SEMANTIC WEB TECHNOLOGY

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Supervisors
Associate Professor Dave Parry
Dr. Quan Bai
Prof. Ajit Narayanan

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By
Seyedamal Zolhavarieh
School of Engineering, Computer and Mathematical Sciences

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Declaration

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Signature of candidate

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Abstract

While the discovery of new clinical knowledge is always a good thing, it can lead to difficulties. Health experts are required to actively ensure they are informed about the latest accurate knowledge in their field. Many health experts already have access to Clinical Decision Support Systems (CDSSs). These systems aid health experts in making decisions by providing clinical knowledge. CDSS is helpful, but often has issues with the quality of knowledge extracted from knowledge sources (KSs) for decision making.

Discovery of high quality clinical knowledge to support decision making is difficult. This issue is partly due to the enormous amount of research, guideline data and other knowledge published every year. Available KSs (e.g PubMed, Google scholar) are very diverse in terms of formats, structure, and vocabulary. Clinical knowledge may need to be extracted from these diverse locations and sources. To facilitate this task, many health experts focus on developing methods to manage and analyse clinical knowledge in this changeable environment. Most of KSs suffer from a lack of proper mechanism for identifying high quality knowledge. For example the PubMed search engine does not fully check some important knowledge quality metrics (QMs) such as citation, structure, accuracy and relevancy.

This research has potential to make decisions easier, save time, and in turn allows the CDSSs operate more effectively. The objective of this research is to propose a knowledge quality assessment (KQA) approach to discover the high quality clinical

knowledge needed for the purpose of decision making. Semantic Web (SW) technology has been used in the approach to assess how qualified knowledge is about given query. The candidate knowledge QMs were identified from related work to improve assessment of knowledge quality in CDSSs. By running a survey, the candidate knowledge QMs were reviewed and rated by health experts. Based on the survey results the knowledge QM measurements were proposed.

While at an elementary stage and considered to be a "proof of concept", this research offers fresh insights into what the world of healthcare will look like when knowledge quality assessment mechanism for knowledge acquisition of CDSSs is fully implemented.

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List of Abbreviations

ACHI	Australasian College of Health Informatics
AD	Alzheimer's Disease
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
AI-RHEUM	Artificial Intelligence Rheumatology
API	Application Programming Interface
BCF	Breast Cancer Follow-up
CDSS	Clinical Decision Support System
CHS	Class Hierarchy Similarity
CP	Class Position
CPG	Clinical Practitioner Guideline
CS	Class Similarity
CTV3	Read Codes, Clinical Terms Version 3
CUI	Concept Unique Identifier
DAML+OIL	DARPA Agent Markup Language-Ontology Interface Layer
DL	Description Logics
ED	Edit Distance
EHR	Electronic Health Record
HiNZ	Health Informatics New Zealand
HL7	Health Level Seven
ICD-10	The International Classification of Disease tenth revision
IHTSDO	International Health Terminology Standards Development Organization
KA	Knowledge Acquisition
KB	Knowledge Base

KE	Knowledge Engineering
KM	Knowledge Management
KQA	Knowledge Quality Assessment
KQI	Knowledge Quality Indicator
KRS	Knowledge Relevancy Score
KS	Knowledge Source
KW	Knowledge Weight
LLC	Lowest Level Class
LM	Learning Management
LOINC	Logical Observation Identifiers Names and Codes
LR	Literature Review
LS	Lexical Similarity
ML	Machine Learning
M-OH	Medical and Oral Health
NCBI	National Centre for Biotechnology Information
NCBO	National Centre for Biomedical Ontology
NHSCCC	National Health Service Coding and Classification Centre
NLP	Natural Language Processing
OWL	Web Ontology Language
PMID	PubMed Identification
QM	Quality Metric
RADLEX	Radiology Lexicon
RCD	Read Codes
RDF	Resource Description Framework
RDFS	RDF Schema
RS	Relationship Similarity

RSNA	Radiological Society of North America
SNOMED-CT	Systematized Nomenclature of Medicine-Clinical Terms
SOA	Service Oriented Architecture
SS	Semantic Similarity
SW	Semantic Web
SWAN	SW Applications in Neuromedicine
SWRL	Semantic Web Rule Language
TF-IDF	Term Frequency-Inverse Document Frequency
UI	User Interface
UMLS	Unified Medical Language System
URI	Uniform Resource Identifier
W3C	World Wide Web Consortium
WSDL	Web Service Description Language
WSMF	Web Service Modelling Framework
WSML	Web Service Modelling Language
WSMO	Web Service Modelling Ontology
WSMX	Web Service Execution Environment
XML	Extensible Markup Language

Chapter 1

Introduction

1.1 Introduction

This thesis is concerned with the importance of knowledge quality for use in Clinical Decision Support Systems (CDSSs). This chapter gives an overview of the thesis. It presents the background and motivation, research objectives, questions and hypothesis, thesis contribution, and thesis structure. Section 1.2 covers the aim of the work. Section 1.3 discusses the original contribution of this thesis. Section 1.4 provides the background and motivation of the work. Section 1.5 discusses the research objectives, questions, and hypothesis. Section 1.6 presents the research design. Finally, Section 1.7 describes the structure of the thesis. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

1.2 Aim of the work

This thesis focuses on the healthcare domain and especially Knowledge Acquisition (KA) in CDSSs. The aim of this work is to determine a Knowledge Quality Assessment (KQA) approach to discover high quality clinical knowledge for the purpose of decision making. The KQA has access to a central knowledge repository as well as electronic knowledge sources such as PubMed. Semantic Web (SW) technology has been used in the approach to discover knowledge and assess the quality of that knowledge. The work aims to improve the KA mechanism for CDSSs.

1.3 Thesis contributions

This thesis provides several original contributions, founded on the success of this investigation. The contributions are discussed in-depth in Chapter 7. The original contributions are listed here in summary:

- Identifying knowledge Quality Metrics (QMs) for discovering high quality knowledge for the decision making process. Publications on this topic include:
  - **Zolhavarieh S**, Parry D. *Discovering Quality metrics for Knowledge Quality Assessment for Clinical Decision Support System.* 15th Annual HiNZ Conference; 2016; New Zealand: HiNZ.
  - **Zolhavarieh S**, Parry D. *Can clinical decision support systems (CDSS) cope with rare or unusually presenting diagnoses?* New Zealand: Conference on Interdisciplinary Innovation and Collaboration; 2016
- Proposing and developing the KQA approach to extract and evaluate the quality of knowledge for using in CDSSs. See:
  - **Zolhavarieh S**, Parry D. *A model of knowledge quality assessment in clinical decision support system.* 14th Annual HiNZ Conference and Exhibition; New Zealand: HiNZ; 2015.
  - **Zolhavarieh S**, Parry D. *KQA: A knowledge quality assessment model for Clinical Decision Support Systems*. MedInfo; 2017

- Representing the benefits of using SW technologies that provide an intelligent structure for representing, sharing, storing, and analyzing knowledge in CDSSs. This topic has been discussed in:
  - **Zolhavarieh S**, Parry D, Bai Q. *Issues associated with the use of Semantic Web Technology in Knowledge Acquisition for Clinical Decision Support Systems: Systematic Review of the Literature. JMIR Med Inform.* 2017. doi:10.2196/medinform.6169
- Developing a knowledge browser to demonstrate the effectiveness of the approach with testing over a real world knowledge source. This is supported by the Precision Driven Health (PDH) Organization. It has been described in:
  - **Zolhavarieh S**, Parry D. *Knowledge browser for discovering high quality knowledge*. New Zealand: Precision Driven Health; 2017

1.4 Background and motivation

Decision making is a core activity for clinicians in the healthcare domain. Since 1954, CDSSs have been developed to enhance health care systems and improve human decision making (Miller, 1994). A CDSS is a particular type of decision support system (Power, 2002) that supports health experts in the decision making process via electronically stored clinical knowledge (Kotze & Brdaroska, 2004; Bonney, 2009). These systems might use different approaches to assist patients, such as using alerts, reminders, interpretation systems, etc. The CDSS has a Knowledge Base (KB), inference/reasoning engine, and user/communication interaction (O'Kane et al., 2010). It receives patient data and an inquiry as inputs and generates a needed knowledge as an output for decision making process (See Figure 1.1). In this scenario, the KB plays an important role in collecting, classifying and sharing knowledge (Leuf, 2006).

A KB is a machine-readable centralized repository for publishing knowledge on-line or having the capacity to be on-line. The KB can be used to retrieve and optimize the knowledge of an organization such as a public library, or a database of particular subjects. In the healthcare scenario, the need for symbolically encoding concepts has led to the construction of knowledge-based systems to facilitate decision making processes. The KB is embedded in the CDSS and is constructed from different knowledge sources(KSs)(See Figure 1.1). A KS is an on-line repository that collects and categorizes knowledge. There are many KSs in the healthcare domain such as PubMed, Mesh, TOXNET, and various electronic textbooks and databases. The process of capturing knowledge from KSs is called Knowledge Acquisition (KA)(Szulanski, 1996).

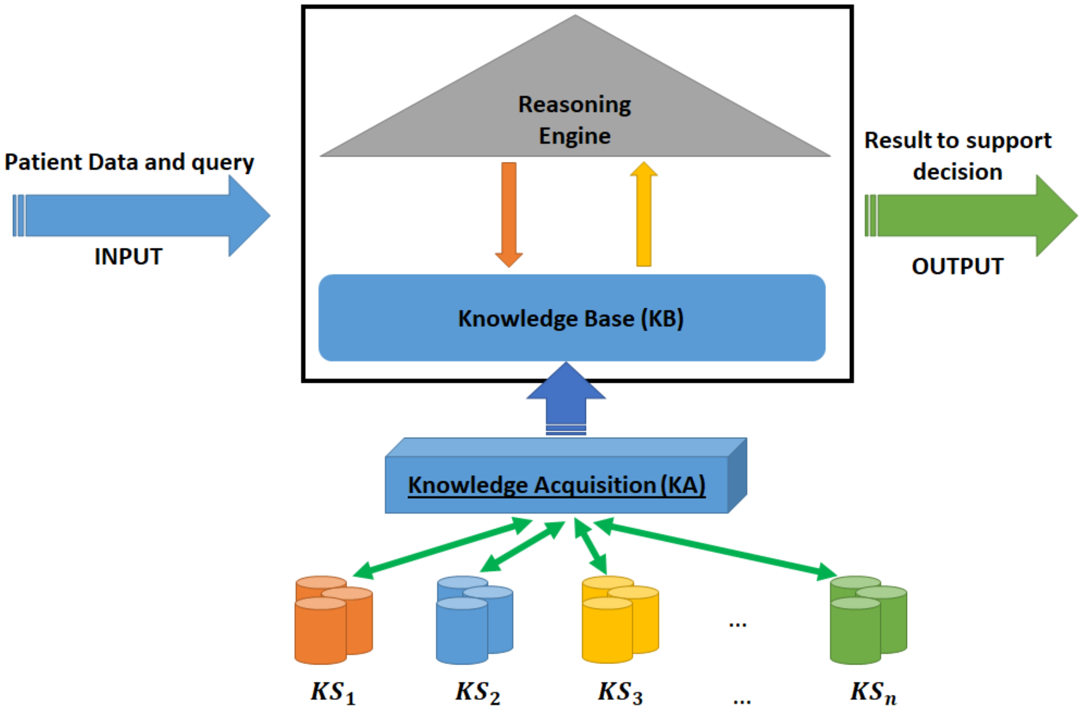

Figure 1.1: The structure of a CDSS

The KA bottleneck is a well-known issue in CDSSs (Hayes-Roth, Waterman & Lenat, 1984). It is vital to provide an appropriate platform for the interaction of the KB of CDSSs with KSs. Every CDSS relies on high quality knowledge retrieved from KSs and stored in the KB. It is essential to provide up-to-date, relevant, and accurate knowledge for health experts. Therefore, it is important to discover high quality knowledge from the KSs. High quality knowledge means less time is wasted looking at unhelpful information when making decisions. This also decreases the likelihood of mistakes being made.

The CDSS would not be effective if it used out of date, limited or incomplete knowledge (von Krzysztof Michalik & Kielan, 2013). Finding the latest accurate clinical knowledge to support decision making is difficult. This issue is partly due to the enormous amount of research, guidelines and other knowledge published every year (Lu, 2011). Clinical knowledge may need to be extracted from diverse locations and KSs that share knowledge in different formats. To facilitate this task, many biomedical researchers are looking to develop methods to manage and analyse clinical knowledge in this changeable environment (Miller, 1994; Cheung, Prud'hommeaux, Wang & Stephens, 2009; Sartipi, Yarmand, Archer & Jao, 2011). One of the more recent technologies that have been applied to KA is SW technology (Wroe, 2006). This technology remedies the problems of knowledge management, representation, and interoperability of KSs.

Knowledge experts have developed some SW-based systems such as COCOON (Della Valle & Cerizza, 2005), ARTEMIS (Bicer, Laleci, Dogac & Kabak, 2005), Semantic-DB (D Pierce et al., 2012), Knowledge-Centric Clinical Decision Support Systems (Hussain, Abidi & Abidi, 2007; Mohammadhassanzadeh, Van Woensel, Abidi & Abidi, 2016), detecting Alzheimer's disease (AD) (Sanchez, Toro, Carrasco, Bonachela et al., 2011), Semantic-CT (Huang, Ten Teije & Van Harmelen, 2013), shareable CDSS (Zhang, Gou et al., 2016), etc. Most existing methods suffer from a lack of a proper mechanism for identifying high quality knowledge from KSs. There is now the question: "How can we ensure that the knowledge used by CDSS is reliable?" To answer this question, this thesis is concerned with the use and selection of new knowledge extracted from KSs and focuses on representation of that knowledge. The element of CDSS that this thesis is concerned with presented in Figure 1.1 as “Knowledge Acquisition (KA)”. This thesis aims to describe an approach called KQA which discovers high quality knowledge from clinical KSs to serve CDSSs. The proposed approach takes advantage of SW technologies.

1.4.1 Motivating example for the research

The motivation for this investigation has been inspired by a real-world example found in the PubMed search engine. Consider the following Web query, which is about “Tuberculosis Arthritis” shown in Table 1.1. The query searches for the recent and up-to-date knowledge related to “Tuberculosis Arthritis” as a clinical term. The discovered knowledge can support clinicians in the decision making process.

Table 1.1: A sample query in PubMed

[Title/Abstract]	Tuberculosis Arthritis
[Language]	English

The PubMed search engine extracts 18 relevant knowledge items for the above query. Although the knowledge items are valid, the question is “How does the user select the most relevant and accurate knowledge to use in the decision making process?”. By checking the abstract/title of the knowledge items (e.g. textual articles), it was discovered that some knowledge items ranked at the top of the search results contained too short information to be used in decision making process. This research has been conducted by two main assumptions for assessing the quality of knowledge: (1) using knowledge item’s abstract, and (2) using MeshHeading which are the index terms used in the Extensible Markup Language (XML) format of PubMed knowledge source. The decision to consider the abstract of the article was based on Wilczynski, McKibbon and Haynes (2001). This work showed that analysis of the abstract for relevance gives similar results to analysis of the entire document. The MeshHeading used in the XML files can contain appropriate meta-data that can be utilized for assessing the knowledge. By considering abstract of knowledge item, if the abstract does not satisfy quality measurements proposed in this thesis, then the knowledge item will get a lower rank for using in decision making process.

Figure 1.2 shows a fragment of the result achieved by the query searched in the PubMed. “Tuberculosis arthritis: A review of 27 cases” (knowledge item 10) is ranked above “Advanced imaging of Tuberculosis arthritis” (knowledge item 12). Because the knowledge item 10 does not contain an abstract and explanation related to the query, it gets lower rank in the ranking list for sorted knowledge items.

Based on this observation, this thesis proposes an approach to discover knowledge and assess the quality of that knowledge for the decision making process. The proposed approach also ranks extracted knowledge based on QMs.


10. Tuberculosis arthritis: A review of 27 cases.
Al-Saleh S, Al-Arfaj A, Naddaf H, Memish Z.
Ann Saudi Med. 1998 Jul-Aug;18(4):368-9. No abstract available.
PMID: 17344697
Similar articles

11. Septic arthritis in patients with human immunodeficiency virus.
Zalavras CG, Dellamaggiora R, Patzakis MJ, Bava E, Holtom PD.
Clin Orthop Relat Res. 2006 Oct;451:46-9.
PMID: 16906073
Similar articles

12. Advanced imaging of tuberculosis arthritis.
Leigh Moore S, Rafii M.
Semin Musculoskelet Radiol. 2003 Jun;7(2):143-53. Review.
PMID: 12920652
Similar articles

Figure 1.2: A sample result from PubMed

1.5 Research Objectives, Research Questions, and Hypothesis

The following sets out the research objectives, research questions, and hypothesis.

1.5.1 Research Objectives

Based on above discussion, this research aims to achieve the following objectives:

- To identify knowledge QMs for the assessment of quality of clinical knowledge extracted from KSs.
- To review literature concerned with how knowledge quality assessment based on SW technology can be useful for decision making.
- To design an approach that can extract knowledge from KSs and assess its quality to facilitate KA and provide better decision making.
- To develop a software system that retrieves high quality knowledge for CDSSs.
- To integrate SW technologies into KQA for the discovery of knowledge for CDSSs.

1.5.2 Research Questions

Based on the above objectives, four questions have been derived as follows:

1. What kind of QMs would be useful for assessing the quality of clinical knowledge extracted from knowledge sources?
2. How SW technologies can be used effectively to support CDSSs?
3. Which annotations are useful in improving clinical knowledge for CDSSs using SW technologies?
4. How can QMs be measured to provide high quality clinical knowledge through SW technology?

1.5.3 Hypothesis

The hypothesis of this thesis is as follows:

1. A SW-based KA system which can assess knowledge quality for CDSSs is possible.
2. Assessing the quality of knowledge is a critical gap for KA in the CDSSs. This work closes this gap to help health professionals in their decision making.
3. The proposed QMs are useful for assessing quality of knowledge.
4. This research proposed an automatic tool for knowledge discovery and knowledge quality assessment.
5. This research has the potential to make a healthcare professional's decision making process easier, save time, making the CDSS to operate more effectively.

1.6 Research design

Several methodologies are used at different stages throughout the thesis. A questionnaire of health experts is used to rate and validate knowledge QMs for the decision making process. The results achieved by the questionnaire shows the importance of knowledge QMs. Recruitment of participants was carried out using a Snowball methodology. Survey analysis and interpretation were carried out using statistical analysis for the rating exercise. Development of a model for KQA for CDSS employed SW technology. Demonstration of the KQA approach and other required functionality was carried out using a prototype methodology, as prototyping is well suited to demonstrating of concepts via software implementation. Overall, this thesis has a progression from the ideas to an actual set of working tools. The research design is explained in detail in Chapter 3.

1.7 The Structure of this thesis

The remainder of the thesis is structured as follows:

Chapter 2 includes a literature review and background to the problem. The review covers some of the basic concepts of CDSSs such as types of CDSSs and SW-based CDSSs. It also explains the importance of utilizing SW technologies. The chapter also categorizes recent issues pertaining to KA for CDSSs. The result of reviewing recent related work has been discussed and concluded as the main motivation for this research, which is a lack of knowledge quality assessment in CDSSs.

Chapter 3 covers the research methodology used in this thesis. The chapter presents the research design which has been divided into four steps: Identify and analyze the problem, define objectives, design and develop the model, and evaluate the approach.

Chapter 4 explains the process of extracting and generating knowledge in the SW-based structure i.e. the ontological structure. This chapter discusses how textual knowledge extracted from KSs can be transferred into the ontological structure to facilitate the process of machine knowledge assessment. This chapter illustrates different processes of extracting and discovering knowledge. It then discusses different concepts used in an ontological structure. Finally, the chapter explains the process of constructing an ontological knowledge.

Chapter 5 deals with the applicability of the development of KQA for assessing the quality of knowledge to be used in CDSSs. In this chapter, knowledge QMs have been formally defined and modeled. The evaluation of knowledge quality using QMs is discussed in detail.

Chapter 6 describes and discusses the results obtained by the KQA approach.

Chapter 7 discusses and assesses how the research questions have been answered, highlights the contribution of the thesis, summarizes the thesis and provides recommendations for future work.

Chapter 2

Literature Review

2.1 Introduction

This chapter introduces literature concerned with the benefits of using SW technologies in CDSSs to improve KA as well as those works which define knowledge quality issue for CDSS. In the introduction section, some concepts used throughout the thesis are explained. Section 2.2 shows that decision making is an essential activity in the healthcare domain. It also introduces some of the concepts behind CDSSs. Section 2.3 gives background related to KA in CDSSs. Section 2.4 discusses the issues addressed in CDSSs. Section 2.5 provides a broad introduction to the literature on SW-based CDSSs. The main purpose of this section is to discuss how SW technologies can support and improve the performance of CDSSs in the healthcare domain. Section 2.6 gives a review of knowledge quality research to find the QMs for checking and evaluating the quality of knowledge. Section 2.7 discusses the main motivation of this research. The goal of this section is to highlight the main limitation of current SW-based CDSSs, which is the lack of a quality assessment system to check the quality of the clinical knowledge used in CDSSs. Finally, Section 2.8 summarizes the concepts discussed in the chapter. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

2.1.1 Background to the knowledge

It is essential for any activity to use sound knowledge (Groff & Jones, 2012). A knowledge paradigm is shown in Figure 2.1 (Aamodt & Nygård, 1995). This figure has been used as the basis for understanding the use of knowledge in computer science.

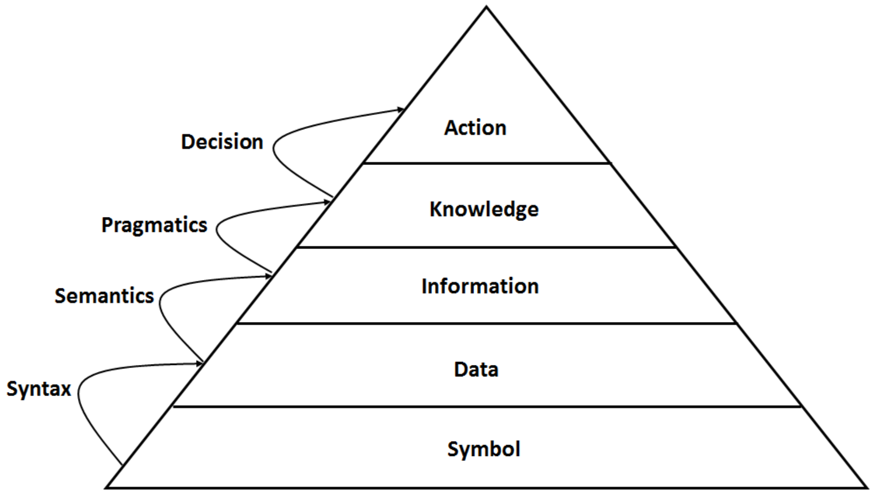

Figure 2.1: Knowledge Pyramid based on Aamodt and Nygård (1995)

There is no fundamental difference in the presentation of data, information, and knowledge in computer science terms. To obtain a visible differentiation between data, information, and knowledge, we need to use different symbols in terms of syntax, semantics, and pragmatics. Data is raw fact, while information has meaning to the user. For example, the number '50' is a datum and has a particular syntax. The data has no meaning unless accompanied by added semantics such as '$', which makes it a price. However, this is simply information, and noone can operate solely based on this information. Only the addition of pragmatics leads to knowledge that is usable for making decisions and taking action (e.g., to buy this item you need to pay $50). Most computer science fields use this interpretation of knowledge as discussed above.

2.1.2 What is an Ontology?

The term “Ontology” (Greek. On = being, logos = to reason) was originally used in philosophy. The term being first coined in the 17th century. Ontology is synonymous with metaphysics or "first philosophy" as defined by Aristotle in the 4th century BC. As metaphysics came to include other fields (e.g., Philosophical cosmology and psychology), ontology has become the preferred term for this field. The use of the term ontology in computer science has a more practical meaning than its use in philosophy. A review of metaphysical ontology is not necessary in computer science, but properties of a machine must have it as basis in order to handle questioned data within a certain domain of discourse. Here, ontology is used as the term for a certain artifact. Tom Gruber’s widely cited response to the question: “What is Ontology?” is: “Ontology is a specification of a conceptualization”. In Gruber et al. (1993), this statement was elaborated on; “A body of formally represented knowledge is based on a conceptualization: the objects, concepts, and other entities that are assumed to exist in some area of interest and the relationships that exist between them. Conceptualization is an abstract, simplified view of the world that we want to represent for some purpose. Every knowledge-based system is committed to some conceptualization, explicitly or implicitly”. Specification means in this context, an explicit representation by some syntactic means. Maedche and Staab (2001) introduced different types of ontologies:

1. ***Top-level ontologies*** aim at describing extremely general concepts such as event and action. It provides top-level ontologies for large communities.

2. ***Domain ontologies*** and ***task ontologies*** describe the vocabularies related to a generic domain such as health or a generic function. The Unified Medical Language System (UMLS) and Systematized Nomenclature of Medicine Clinical Terms (SNOMED-CT) are an example of domain ontologies.

3. ***Application ontologies*** illustrate dependent concepts related to individual roles played by domain entities for the purpose of performing a particular activity.

Note that the distinction between domain ontologies and other ontology types is sometimes useful, but by no means, a strict classification: by adjusting the field, every ontology can be classified as a domain ontology. The ontology contains a set of relevant concepts (i.e. classes) and the relationship between those concepts that can be classified in the hierarchical structure. For example, in an organization such as a university, staff members, students, lecturers, and courses are some important classes in the ontology of the university. A specific property can identify the relationship between classes and subclasses. The disjointed statement is another kind of property which indicates that two concepts in the hierarchy are separate e.g. faculty and general staff in university ontology are disjointed.

To create an adequate ontology of a particular domain, the ontology construction should be supported by (1) the use of a methodology that guides the ontology development process and (2) tools to inspect, browse, code, modify and download the ontology. The most popular ontology languages are Resource Description Framework (RDF), RDF Schema (RDFS), and Web Ontology Language (OWL). RDF is a primitive data model for classes (Subject and Objects) and the relationships (Predicates) between them. It provides simple semantics for a data type that can be serialized in the XML syntax. The second one, RDFS is a vocabulary description language along with semantics for generalization hierarchies of such properties and classes. OWL is a richer vocabulary description language for explaining classes and properties (predicates). All of the ontologies used in this research are based on the OWL language.

2.1.3 OWL language

OWL is the latest standard ontology language supported by the World Wide Web Consortium (W3C) to promote the SW vision. It is developed as a vocabulary extension of RDF and RDFS and is derived from the DARPA Agent Markup Language Ontology Interface Layer (DAML+OIL) language (Parsia, Fokoue, Haase, Hoekstra & Sattler, 2009). OWL is used to describe elements (classes, properties, and individuals) and their relationships with each other by utilizing the Web as a medium for sharing knowledge. The elements and relationships are defined as RDF resources and distinguished by Uniform Resource Identifiers (URI). The formal semantics of the OWL language helps machines to understand facts which are not presented in the ontology.

2.1.4 Ontology editors

Ontology editors are applications to help in ontology generation or manipulation. There are many ontology editors to be found on the internet. Some of the most popular ontology editors are Apollo, Protégé, OntoStudio, TopBraid, and Swoop. A screenshot of the Protégé-OWL ontology editor is given in Figure 2.2. In this thesis, the Protégé ontology editor will be used to construct knowledge. The Protégé is an open-source platform that helps users construct domain models and knowledge-based applications with ontologies. As this research utilizes the OWL language, Protégé-OWL is the version of this editor utilized. Protégé provides a rich set of knowledge-modeling structures and actions that support the creation, visualization, and manipulation of ontologies in various representation formats. It can be customized to provide domain-friendly support for creating knowledge models and entering data. It can also be extended with a plug-in architecture and Java-based Application Programming Interface (API) for building knowledge-based tools and applications. Protégé allows for the definition of classes, class hierarchy variables, variable-value restrictions, and the relationships between classes and the properties of these relationships.

2.1.5 Ontology repositories

Updating or creating new knowledge, and sharing and reusing ontologies are major aims of ontology engineering. For this reason, ontology resources have been made available on the web for future use. For example, BioPortal (ontology repository of National Centre for Biomedical Ontology (NCBO)) is an open repository of over 300 biomedical ontologies available on the web, developed in different languages and formats, such as OWL and RDF. There is a specific frame for this repository in Protégé that provides access to the ontologies. It also provides access to ontologies on the web to help users search, browse and review ontologies. It also supports searches of biomedical resources such as PubMed for a combination of terms from ontologies.

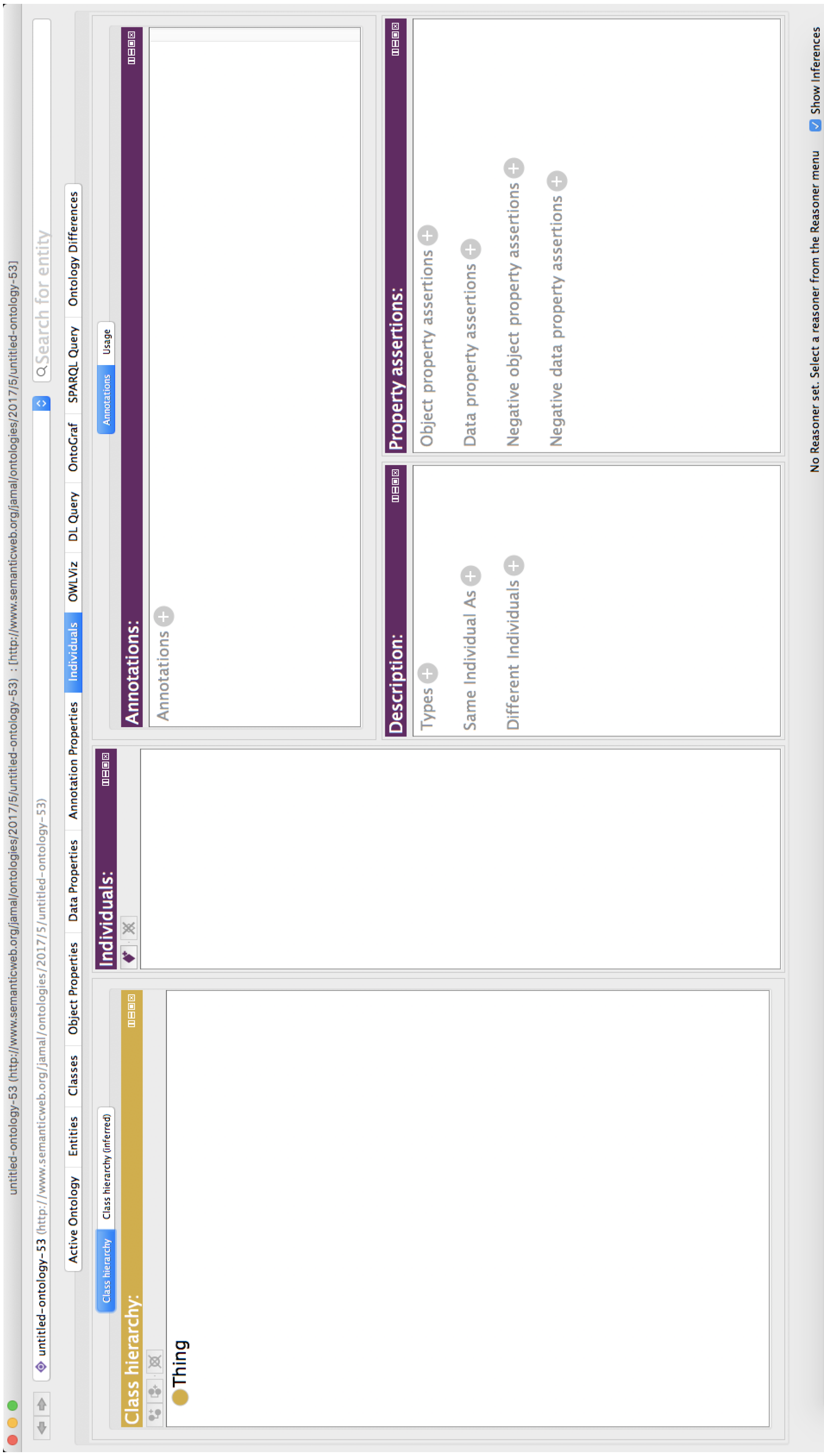

Figure 2.2: A screenshot of the Protégé-OWL ontology editor

2.2 Clinical Decision Support Systems (CDSSs)

Decision making is a fundamental activity for clinicians. It is a daily process for all practitioners to make decisions about patient care. Such decisions are critical. The quality of decisions depends on how much experience experts have and how much accurate knowledge is available. Clinical decision making is a complex activity and requires clinicians to have access to relevant, up-to-date and accurate knowledge sources to support appropriate patient care.

Sharing clinical knowledge meaningfully and safely has been a goal of health providers around the world. To this end, CDSSs have been developed to enhance healthcare systems and improve human decision making (Miller, 1994). The development of CDSSs are growing very fast for three main reasons: 1) ever growing clinical knowledge to access, 2) the provision of clinical knowledge in a meaningful format, and 3) the ability to develop a personalized decision making system (Musen, Middleton & Greenes, 2014). A good CDSS can be characterized by the five 'rights': 1) providing the right knowledge, 2) to the right person, 3) in the right format, 4) via the right channel, 5) at the right point in the workflow to enhance healthcare decisions.

2.2.1 Types of CDSSs

The following are some common types of CDSSs introduced in detail. These types of CDSSs consist of info-buttons, branching logic, probabilistic systems, rule-based systems, ontology-driven CDSSs, data-driven CDSSs, and knowledge-driven CDSSs.

Info-buttons

The most popular model of CDSSs utilizes contextual information retrieved from an Electronic Health Record (EHR) database. In the EHR of any patient, there might be scalable icons as info-buttons next to other records such as patient history, laboratory tests, and patient' medication. Clicking on the info-button generates a query on the database to provide more informative resources about items in the query. The query might provide contextual information from those resources that have been involved in the healthcare process such as physicians, nurses, and so on. Although info-buttons are valuable knowledge resources, many users believe that they do not make the CDSSs intelligent enough. The info-buttons provide related information for a user query, but they are not accurate enough to be used in decision making (Cimino, Li, Bakken & Patel, 2002).

Branching Logic

Several CDSSs have provided specific flowcharts which have been designed and encoded to computer interpretation applications. Although these algorithms are beneficial for patients in urgent situations, they are generally ignored by most clinicians. It is important to know that using a flowchart is not sufficient for decision making. To make this platform more professional, combining branching logics with clinical protocols and guidelines to generate heterogeneous knowledge for CDSSs is possible (Bleich, 1972; Grimm Jr, Shimoni, Harlan Jr & Estes Jr, 1975; Komaroff et al., 1974).

Probabilistic Systems

A considerable amount of research has been conducted on applying Bayesian diagnosis programs to explain patients' conditions.De Dombal et al. adopted a naïve Bayesian model (De Dombal, Leaper, Horrocks, Staniland & McCann, 1974). The model assumes that there is not any conditional dependency among findings. In this regard, there are many supervised learning techniques such as decision trees, regression analysis and support vector machines that have been used to extract knowledge from an EHR database (Saria, Rajani, Gould, Koller & Penn, 2010; Kahn, Roberts, Shaffer & Haddawy, 1997; Sox, 1988; Pauker & Kassirer, 1981; Knaus, Wagner & Lynn, 1991).

Rule-based Systems

Developers have applied rule-based approaches to improve the level of query performance in CDSSs (Knaus et al., 1991; Clancey, 1993; Downs, Biondich, Anand, Zore & Carroll, 2006; Dupuits, 1994). Technically, rule-based systems need a formal language for encoding rules along with an inference engine to produce answers. An example of a rule-based system is MYCIN (Shortliffe, 2012), which uses a rule-based approach using the Lisp programming language. The MYCIN has an inference engine to interpret and evaluate the truth value of rules that should be represented in the final result. Although MYCIN is constructed based on the particular syntax for encoding, interpreting and evaluating rules, there are many open source engines such as JESS that execute rules at the same runtime. JESS is a popular Java-based rule engine produced at Sandia National Laboratory. Another popular rule-based system is the HELP system which provides alerts or reminders to a particular clinician or other team member.

Ontology-Driven CDSS

Developers have begun to generate ontologies of clinical guidelines. The guideline ontology is adopted based on the healthcare requirements. This guideline must provide proper criteria for patient treatment, such as drug guidelines that indicate the medications to be administered to patients. Ontology-Driven CDSSs are proposed to extract an abstracted level of clinical knowledge in order to overcome limitations in the CDSS architecture. Ontology-Driven CDSSs provide an opportunity to make a decision based on the statistical knowledge and the patient-specific problem. It can be used particularly for chronic disease patients (Musen et al., 1998; De Clercq, Blom, Korsten & Hasman, 2004; Fieschi et al., 2004; Lin et al., 2006; Gennari et al., 2003; Trafton et al., 2010).

Data-driven CDSS

Data-driven CDSS is based on live-stream clinical data from the system and an artificial intelligence engine. It detects patterns by applying some data mining and decision making methods. Each method cannot work alone. Therefore developers propose real-time systems to support the decision making process (Chou, 2012).

Knowledge-Driven CDSS

Extracting knowledge from large KSs is one of the most critical areas in health informatics. To provide a knowledge sharing environment, this CDSS can store and reuse knowledge and generate rules and predictions. The target system will use a Knowledge Management (KM) mechanism and Artificial Intelligence (AI) tools to deliver knowledge items for decision making. A system which can deliver these properties is called a knowledge-driven CDSS. This type of CDSS provides some recommendations for clinicians based on extracted knowledge (Kamaleswaran & McGregor, 2012). Knowledge–driven CDSSs use machine-stored knowledge to assist clinicians. Other CDSSs may learn from large amounts of data via Machine Learning (ML) techniques, or act as a case–based reasoning system (Groff & Jones, 2012). In this thesis, we have focused on knowledge-driven CDSSs.

2.2.2 Standard Clinical Terminologies

A standard clinical terminology is an essential part of all clinical systems, enabling the practitioners to record patient data consistently, which is then able to be shared efficiently between different systems used by health experts. The following briefly explains some common standard clinical terminologies.

Systematized Nomenclature of Medicine-Clinical Terms (SNOMED-CT)

SNOMED-CT is one of the most popular standard clinical terminologies (Donnelly, 2006). It is maintained by the International Health Terminology Standards Development Organization (IHTSDO). It has comprehensive, multilingual vocabularies of clinical terminologies that can be used effectively in different healthcare systems. SNOMED-CT is a concept-based and general medical terminology. In this terminology, any concept can be represented by more than one term. Wroe (2006) discusses the lack of enough semantic clinical data in the healthcare system. To this end, the study points to the possibility of representing SNOMED-CT concepts in the OWL language as OWL classes, and various terms used to denote those classes can be represented using RDFS labels where required. As previously mentioned, OWL is a family of knowledge representation languages for describing and enriching taxonomies, emerging from the SW technology. Wroe (2006) proposed an approach to use the OWL language to enrich and develop clinical terminologies.

Logical Observation Identifiers Names and Codes (LOINC)

LOINC is a universal terminology to identify medical laboratory observations (McDonald et al., 2003). It utilizes codes and terminologies to improve EHR identification. In 1999, the Health Level Seven (HL7) standards were developed for this type of clinical terminology to answer the clinical demands of laboratory tests, observation, and research.

Read Codes, Clinical Terms Version 3 (CTV3)

CTV3 is a standard terminology for describing the care and treatment of patients, which includes hundreds of thousands of terms, synonyms, and abbreviations covering popular concepts related to patient care (O'Neil, Payne & Read, 1995). Read Codes (RCD) are supported by the National Health Service Coding and Classification Centre (NHS CCC). The RCD is now considered a subset of SNOMED-CT.

Radiology Lexicon (RADLEX)

To facilitate radiologist requirements to organize and retrieve patient medical records, the Radiological Society of North America (RSNA) generates a controlled terminology to support indexing and querying of radiology information called RADLEX (Langlotz, 2006).

The International Classification of Disease tenth revision (ICD-10)

ICD-10 is supported by the world health organization to create a coding system for various medical records. This terminology can analyse health data for population groups (Organization, 1992).

Artificial Intelligence Rheumatology Consultant System Ontology (AI-RHEUM)

One of the smallest terminologies in the healthcare domain is AI-RHEUM which has been used for diagnosing rheumatologic diseases (Kingsland, Lindberg & Sharp, 1983). Clinicians and informatics researchers are using this standard to diagnose illness and assign proper treatment.

2.2.3 Applied methods in CDSSs

Table 2.1 explains the most recent techniques and methods applied to make decisions in different CDSSs.

Table 2.1: Method applied in CDSSs

Method	Description
Linear programming	Linear programming is a method for discovering the best solution satisfying certain limitations by maximizing or minimizing linear functions. Hershey (1991) uses linear programming to determine optimal clinical strategies when event probabilities are not known, but their value chain is available (Testi & Tànfani, 2009).
Inventory models	Inventory models minimize inventory costs by considering optimal values when placing an order or order quantity (Oh & Hwang, 2006).
Integer programming	Integer programming is a mathematical optimization problem that is viewed as a particular model of linear programming where variables are limited to an integer (Eben-Chaime & Pliskin, 1992).
Non-linear programming	Non-linear programming is an optimization problem defined by a system of equalities and inequalities over a set of unknown real variables. The objective of variables is to be maximized or minimized, where some constraints are non-linear (Aspden, Mayhew & Rusnak, 1981).
Dynamic programming	Dynamic programming is a method for solving a complex problem by breaking it down to simpler sub-problems that have an optimal substructure (Hall, 2010).
Queuing	Queuing is a technique for displaying different types of queues to assess their behaviour (Patrick & Puterman, 2007).
Markov	Markov is a stochastic model used to model randomly changing systems where it is assumed that future states depend only on the present state and not on a sequence of events (Sonnenberg & Beck, 1993).
Artificial neural networks	Artificial neural networks are an information-processing paradigm inspired by the structure of biological neural networks and the way they process information (Mangalampalli, Mangalampalli, Chakravarthy & Jain, 2006).
Genetic algorithms	Genetic algorithms is a heuristic search algorithm that depends on the concept and process of natural evolution and selection (Zellner, Rand, Prost, Krouwer & Chetty, 2004).
Game theory	Game theory is a mathematical modelling for games that focus to gain an individual goal that is dependent on the choices of other players. Game theory suggests strategies for enhancing the probability of success (Parsons, Gmytrasiewicz & Wooldridge, 2012).
Decision trees	Decision trees are a visual and analytical tool that contain three main types of nodes: decision nodes, chance nodes, and end nodes (Critchfield & Willard, 1986).
Simulation	Simulation is a process that encompasses simulation approaches for better decision making (Santibáñez, Chow, French, Puterman & Tyldesley, 2009).
Visual interactive modelling	Visual interactive modelling generates animated graphics for target applications. Users can therefore discover more dynamic features of an application for better understanding (Au & Paul, 1996).

2.3 KA as a bottleneck for CDSSs

Recently, informatics researchers have proposed several computerized methods to find relevant and accurate knowledge to assist decision making. CDSS generally requires knowledge to be available, rather than generating its knowledge through ML. Knowledge-based approaches may be more effective in cases where little data for ML is available, or there is a need for an explanatory capacity. Early decision support systems such as MYCIN (Shortliffe, 2012) used knowledge-based approaches, albeit from knowledge collected by experts. However, there are still limitations in their utilization with regard to the need to fit together with the use of clinical experience. The CDSSs may be most useful where the clinician does not have recent knowledge of a particular problem, or may not feel that their knowledge is up-to-date.

The CDSS works by extracting knowledge from various KSs. However, KA is a well-known bottleneck for any CDSS (Hayes-Roth et al., 1984). KA is the process of extracting, structuring and organizing knowledge from different KSs to be used by human experts and intelligent systems (Szulanski, 1996; Gaines, 2013). Gaines provides the background to KA techniques. KA is a necessity for any system as the system cannot be developed without the ability to communicate with external KSs. Generally speaking, KA can be seen as representing a flow of knowledge from external stores of knowledge into the main system.

It is essential to extract knowledge from different KSs (e.g., textual sources, databases, or human experts) and transform this knowledge into a form that can be used to build a knowledge-driven CDSS. Here, the question is; *"how to form an efficient model to acquire, store, and represent the external knowledge?"*

2.4 KA Issues in CDSSs

There are several KA issues for CDSSs; format heterogeneity, lack of semantic definition, lack of data integration, data heterogeneity, and weak semantic infrastructure. These issues have been categorized into two main categories: format and data heterogeneity, and lack of semantic analysis. The following describes these issues briefly.

2.4.1 Format and data heterogeneity

Format and data heterogeneity has been further divided into the following subcategories.

Format heterogeneity

This issue arises from the fact that there are different ways of representing and storing the same data. Due to the variation in data models, connecting various biomedical KSs is not an easy task.

Data heterogeneity

This issue refers to the redundant results for a single entry, such as having multiple entries for the same data.

Lack of data integration

This issue relates to a lack of a unified model for combining data residing in different KSs. Clinical healthcare systems need a unified model in order to be able to share and reuse knowledge.

Reviewing format and data heterogeneity issues, they can be identified as a semantic interoperability issue (Blomqvist, 2014),an important issue defined by Heflin and Hendler (2000). In their definition, semantic interoperability is *"... integrating resources that were developed using different vocabularies and different perspectives on the data.*

To achieve semantic interoperability, systems must be able to exchange data in such a way that the precise meaning of the data is readily accessible and any system can translate the data itself into a form that it understands". It is a critical issue in CDSS, and most current research is focused on developing stronger decision making systems through it (Cheung et al., 2009; Pathak, Kiefer & Chute, 2012; Deus et al., 2008). The semantic interoperability issue is not included in this research's objectives. However, the research method can help enhance the performance of semantic interoperability.

2.4.2 Lack of semantic analysis

This issue has been divided into two subcategories as below.

Weak semantic infrastructure

Lack of a semantic infrastructure, having an effective shared understanding of meaning, reduces the value of results for healthcare KSs.

Lack of semantic definition

Without sufficient semantic definitions, CDSSs are not able to interpret the meaning of extracted knowledge. Such knowledge is usually encoded in the ontology (i.e., schema-level).

2.5 Using SW technology in CDSS

SW technology is an effort to make knowledge available on the web both more easily understand by humans and machine-readable (Burrows, 2013). In the context of CDSSs, there is well-known biomedical research which has used SW technologies (Wroe, 2006; Feigenbaum, Herman, Hongsermeier, Neumann & Stephens, 2007; Tao et al., 2013), and semantic mechanisms (Al-Mubaid & Nguyen, 2006, 2009) to improve the process of KA in CDSSs (Blomqvist, 2014; Pathak et al., 2012; Schulz & Martínez-Costa, 2013; Sonsilphong & Arch-int, 2013). However, it is still unclear how SW technologies can be efficiently used to support KA for CDSS. This section will explain how SW technologies can improve KA issues for CDSS.

2.5.1 SW Technology

The ever-growing amount of data that is being placed on the Web has made it increasingly difficult to find, access, present and analyse information required by users. As Web 2.0 data is presented in a human-readable format, more elaborate mechanisms need to be layered on top of the Web to extract its full potential efficiently. Before Tim Berners-Lee created the World Wide Web, a more powerful hypertext system (e.g. SGMC) was available, but he proposed his simple specifications for publishing raw data as a public standard model. Berners-Lee founded the W3C to oversee these standards. The SW is built on W3C standards consisting of: the RDF data model, the SPARQL query language, and the RDFS and OWL standards for storing vocabularies and ontologies (Antoniou & Van Harmelen, 2004).

SW is simply a new layer on top of Web 2.0. Figure 2.3 displays the "layer cake" model of the SW proposed by Berners-Lee, which depicts the major layers of the SW. As can be seen in this figure, at the bottom, URI indicates everything in the SW with one name identified by one unique URI. The XML layer on top of the URI allows developers to prepare structured web documents. The XML data structure is a suitable way to publish documents on the Web. The RDF data model is a basic principle in the SW structure which helps to represent meaningful relationships by a SPO triple <Subject, Predicate, Object>. Subjects and objects can be represented as nodes of an RDF graph, while predicates are edges or meaningful links between subjects and objects. The RDF data model does not rely on XML, but it can be serialized in XML format, and so the RDF layer is located on top of the XML layer. The main difference between the XML tree and the RDF graph is that edges of the XML tree are unlabelled and undirected, while RDF is a directed, labelled graph.

Soon after proposing the RDF model, developers provided RDFS to organize SW elements into hierarchies. RDFS adds more vocabulary elements to raw RDF graphs, such as classes and properties, subclass and sub-property relationships, and domain and range restrictions. The complexity of relationships among RDF graph elements, created a need for a more powerful ontology language. OWL, a layer on top of RDFS, provides a more flexible representation of the complex relationships between SW elements. The logic layer enhances the ontology language and allows it to represent more specific declarative knowledge. The proof layer works on the deductive process as well as proof validation. The last layer of the "layer cake" model is trust, which involves digital signatures and trust agents' recommendations (Antoniou & Van Harmelen, 2004).

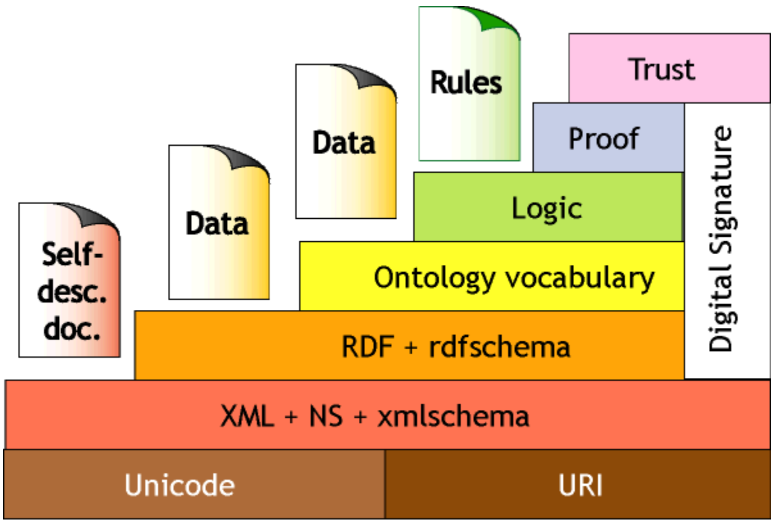

Figure 2.3: "Layer cake" Model of the Semantic Web

Ontology Matching

The current Web contains over a billion pages and most of them are in the human readable format (e.g., HTML). Consequently, computerized applications are not able to easily analyse and process this information. In this regard, researchers have created the vision of the SW where data have been represented in triple format. In the SW, ontologies explain the semantics of the data. By representing data in the ontological structures, the computerized applications can better understand the semantics. Ontology matching is the problem of finding the semantic mappings between two given ontologies to integrate ontologies in a unique structure (Otero-Cerdeira, Rodríguez-Martínez & Gómez-Rodríguez, 2015; Shvaiko & Euzenat, 2013). There exist different methods for finding the similarity among two given ontologies such as string-based techniques, natural language processing (NLP) technique, instance-based technique, constraint-based technique, graph-based technique, and hybrid technique. The string-based technique is one of the popular techniques for ontology matching. The String-based technique usually evaluates the similarity among ontological vocabularies by using string distance metrics such as TF-IDF, Euclidean, Jaccard, etc. David and Euzenat proposed an approach to measure distances between two given ontologies by using string metrics (David & Euzenat, 2008). Another common technique is based on NLP techniques such as tokenization, lemmatization and finding similarity by using thesauri (e.g., WordNet). Some of these methods are applied by G. Shah and Syeda-Mahmood (2004) to the purpose of matching ontologies. In an instance-based technique which is another technique in the ontology mapping, the system assumes that the individuals are alike, then the classes they assign could also be similar (Sánchez-Ruiz, Ontanón, González-Calero & Plaza, 2011). In the constraint-based techniques, the domain and range of the properties or types of attributes will be assessed to check the similarity of two given ontologies (Glückstad, 2010). In the graph-based technique, the system treats the ontologies as a graph homomorphism (Aleksovski, ten Kate & van Harmelen, 2008; Joslyn, Paulson & White, 2009). There exist some hybrid techniques that combine above categories to find similarity among ontologies. GLUE is a semi-automatic system that checks the semantic similarity of two ontologies (Doan, Madhavan, Domingos & Halevy, 2004). In this study, terminological and structural measures have been used for the ontology matching process. Automated Semantic Matching of Ontologies with Verification (ASMOV) is an algorithm that automatically measures the lexical and structural similarity of two given ontologies to overcome semantic heterogeneity among them (Jean-Mary, Shironoshita & Kabuka, 2009).

2.5.2 The KA issues associated with the use of Semantic Web Technology in CDSSs

Figure 2.4 shows how using SW technologies may help to remedy the KA issues of CDSS. SW technology is an efficient way to improve KA as it; provides an intelligent query processing mechanism rather than a keyword-based answering process, provides an easy inference process, organizes the knowledge in conceptual domains, supports consistency, facilitates knowledge extraction, supports data integration as well as semantic interoperability, provides knowledge retrieval, and knowledge representation. The following is a review of recent related work, dealing with SW technologies for improving the KA of CDSSs for the purpose of diagnosis.

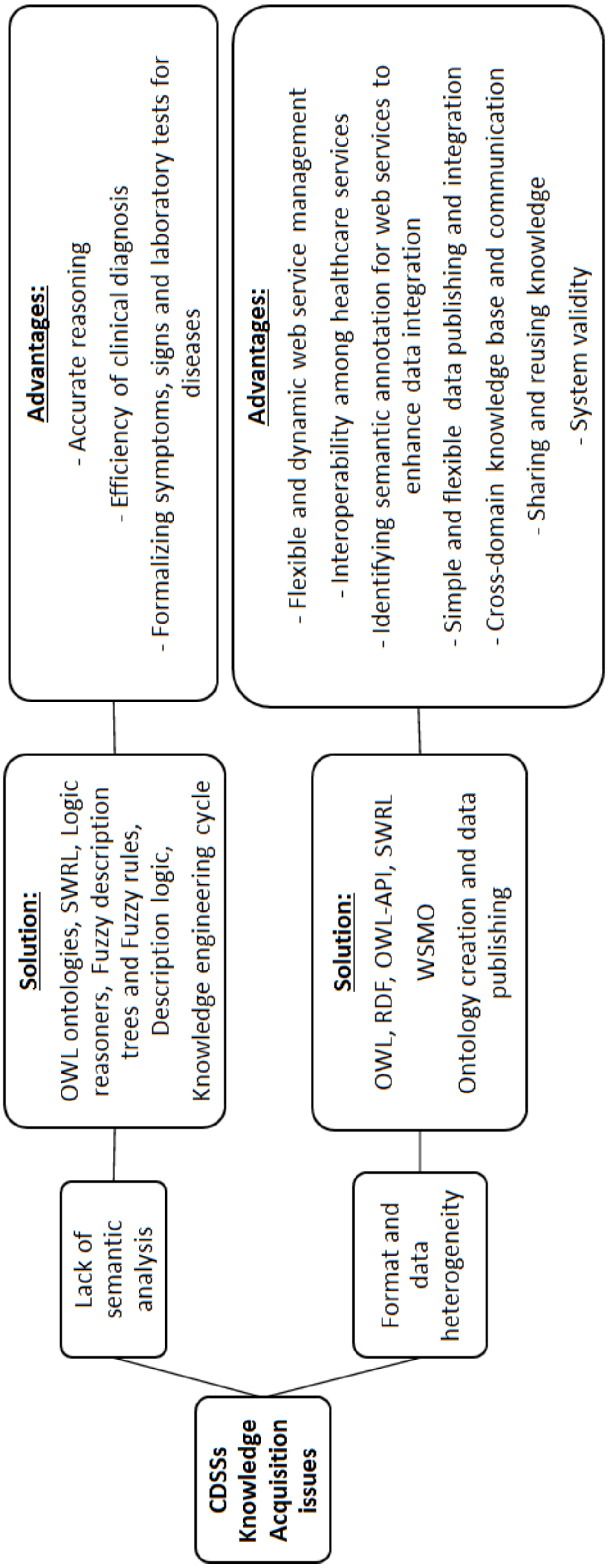

Figure 2.4: The KA issues of CDSSs improved by SW technologies

2.5.3 SW based CDSSs

A literature review (LR) was applied to search, extract, and assess articles, using a keyword search to find relevant articles, containing "Semantic Web Technology" and "Clinical Decision Support System" (see Table 2.2). Note that this section described in JMIR paper (Zolhavarieh, Parry & Bai, 2017). SW technologies started to be used to support CDSSs after 2005, so the search started from that year (Della Valle et al., 2005). To extract related articles, we queried PubMed, Web of Science, Journal of Biomedical Informatics, Knowledge and Information Systems, Journal of Medical Systems, Artificial Intelligence in Medicine, Current Bioinformatics, Journal of Convergence Information Technology (JCIT), IEEE International Conference on e-Health Networking Applications and Services, and Health Science.

By searching both title and abstract of the extracted articles, those papers that deal with concepts of SW technologies and CDSSs together have been considered. While there are many articles that discuss CDSSs, few of these review the importance and benefit of SW technologies in the area of CDSSs. Only papers which strongly focus on improving KA issues in the context of CDSSs through applying SW technologies were considered. Also, the articles that they were not in the English language have excluded. Of the 283 articles, 27 met inclusion criteria. In the following, the SW-based CDSSs have been categorized into two main categories derived from the major KA issues: format and data heterogeneity, and lack of semantic analysis.

Table 2.2: Search terms for reviewing SW based CDSSs

Search Lines	Search Terms	Filtered by
Line 1	"Semantic technology" OR "Semantic Web technology" OR "Semantic Web" OR "Semantic Web techniques" OR "Semantic-based" OR "Semantic-Web-based".	Title/ Abstract
2. AND	"Clinical Decision Support" OR "Clinical Decision making" OR "Medical Decision Support" OR "Medical Decision making" OR "Clinical Decision Support System" OR "Medical Decision Support System" OR "CDS" OR "CDSS".	Title/ Abstract
3. AND	"Architecture" OR "Framework" OR "System" OR "Model".	Title
4. AND	"Health" OR "disease" OR "case study" OR "public health".	Title/ Abstract
5. AND	"Diagnosis" OR "treatment" OR "prediction" OR "reasoning".	Title/ Abstract

SW based CDSSs which improve format and data heterogeneity

It is important to mention that the reviewed papers proposed two different types of framework to overcome the issue of format and data heterogeneity. These frameworks, which has been developed by utilizing SW technologies, are ontologically-based structures and SW services. Through these means, SW technologies have been used to boost the KA process in CDSSs.

Ontologically-based structures

By applying RDF, OWL, and Semantic Web Rule Language (SWRL), researchers have started to utilize SW technologies to empower and facilitate the process of knowledge sharing among CDSSs. An ontology is potentially very useful in SW, as it identifies the relationships between concepts in a domain. One of the most popular approaches for reducing the problem of data and format heterogeneity of CDSSs is therefore to use an ontologically-based structure. Generally speaking, an ontologically-based structure is important for the following reasons (Chandrasekaran, Josephson & Benjamins, 1999; Noy, McGuinness et al., 2001):

- Using an ontologically-based structure enables the process of knowledge sharing, in fact, it helps people and machines to understand the structure of knowledge.
- Using an ontologically-based structure enables the process of reusing knowledge. When an ontology is generated for a system or group, other systems or groups can understand and reuse the ontology creating another. It is also easy to extend the ontological structure when the domain knowledge develops.
- Using an ontologically-based structure separates domain knowledge from operational knowledge. Configuration for a program can be set in accordance with program requirements. This configuration is independent of the program and ontology components.
- Using an ontologically-based structure makes the process of analysing domain knowledge possible once a declarative specification of the terms is available.

Bright, et al. addressed antimicrobial health problems and inappropriate antibiotic prescribing in the healthcare domain. In this study, an application-independent knowledge-driven CDSS model was developed using formal ontological methods. The method used some SW standardizations such as OWL, and SWRL to evaluate the results through intrinsic and extrinsic evaluation studies. However, this study suffers a lack of an accurate evaluation mechanism. The results of the study mostly gathered in a laboratory setting rather than a clinical setting (Bright, Furuya, Kuperman, Cimino & Bakken, 2012).

Dasmahapatra, et al. proposed an ontological mediated decision support system for breast cancer treatment by utilizing SW technologies for the use of data in the decision making process. The benefit of using SW technologies in such systems is its ability to integrate heterogeneous formats of KSs. It also helps in handling complex and large data sets when sharing and reusing knowledge. Although the system is not scalable enough to be used in a large clinical setting, it provides a flexible architecture (Dasmahapatra, Dupplaw, Hu, Lewis & Shadbolt, 2005).

Bio-DASH is a SW-based prototype of a drug development dashboard. In this CDSS, users employ an RDF model to diagnose disease, and search for compounds, drug progression stages, molecular biology and pathway knowledge. This system addressed the problem of sharing heterogeneous knowledge in the CDSSs. To tackle this issue, the authors proposed a SW-based framework using RDF/OWL languages to describe objects and the relationships between them. The framework supports data integration and user authorization. The proposed method suffers from a lack of an appropriate platform for sharing and aggregating knowledge. High memory usage is another drawback of the proposed model (Neumann & Quan, 2005).

Some papers described a proposed Clinical Practitioner Guideline (CPG) CDSSs (Hussain et al., 2007; Abidi, Hussain, Shepherd, Abidi et al., 2007; Jafarpour, Abidi & Abidi, 2011; Hussain & Abidi, 2009). The main idea behind this series of papers is to integrate different types of ontologies such as the domain ontology, CPG Ontology, and patient ontology by developing a knowledge-centric system. This system, which has been developed for the Breast Cancer Follow-up (BCF) community, contains three main components; (1) paper-based BCF CPG computerization, (2) ontology development, and (3) executing BCF CPG in a logic-based engine. Technically, this structure helps to reduce the workload of the specialist cancer center. The simple and flexible usage of data publishing and integration along with user interaction are the advantages of using SW technology in these frameworks. However, the proposed system is quite generic and needs to be validated in different contexts.

Sherimon, et al. offered an ontology-based approach for predicting the risk of hypertension and diabetes in CDSSs. To this aim, the authors used ontologies to represent patient medical profiles and improve an inference mechanism for clinical decision making (Sherimon, Vinu, Krishnan & Takroni, 2013).

Samwald, et al. proposed a SW-based KB for clinical pharmacogenetics to manage data. The KB has been developed by utilizing SW standardizations such as RDF and OWL. The OWL ontology contains the details of drug product labels in regard to pharmacogenomic information. The advantages of using SW technologies have been highlighted in this study. The ontologically-based structure can increase the likelihood of successful long-term maintenance and growth of a KB. It is also valuable for handling a large amount of data sets, sharing and reusing ontological concepts (Samwald et al., 2013).

The Cleveland Clinic supported a project called Semantic-DB (D Pierce et al., 2012) which proposed a framework to collect, store and reuse knowledge to support sufficiency, flexibility, and extensibility of different clinical data. The reliability of research results and the accuracy of quality of care are the issues addressed in this paper. The proposed model contains three main components: (1) content repository, (2) query interface, and (3) data production. The results obtained by the method show that the system can guarantee the quality of care measurements. It has also reduced duplicate effort as well as providing transparency to deduct errors in the reported data. This work needs improvement in regard to ontology alignment, maintaining semantic alignment, and improving performance.

Lastly, Shah, et al. focused on answering the question of how the SW tools, such as ontologies and rules, can be applied to connect the Medical and Oral Health (M-OH) domains through development of a KB. The medical information systems can reuse the KB for semantic interoperability and reasoning process. The system was developed utilizing OWL and SWRL rules. According to the results, effectiveness in reasoning, comprehensive cross-domain KB capability, and cross-domain communication are the strengths of the proposed system (T. Shah, Rabhi, Ray & Taylor, 2014).

SW services

In most Service Oriented Architecture (SOA) applications, human intervention still remains an issue. For example, to explain the semantics of informal descriptions or to harmonize incompatible data schemes. The keywords “Car” and “Automobile” are synonyms, but there is still a lack of semantic recognition as to the similarity of these terms in the structure of the web. The SW Service is a popular concept in the domain of SW technology that helps supply dynamic exploration and knowledge discovery. It uses semantic modelling, semantic methods (such as semantic similarity), and ontology (Blake, Cabral, König-Ries, Küster & Martin, 2012).

SW services are components of the SW. They use markup languages that arrange data in a machine-readable way. SW services modify Web service communication technology in an intelligent way. Ontology-based metadata provides the possibility of integrating applications to support service searching and service schema matching. SW services, like formal web services, are a client–server systems to facilitate machine-to-machine interaction in the World Wide Web (Swartz, 2002).

In the context of SW services, semantic techniques are added to the web services to support Web Service Description Languages (WSDL) (See Figure 2.5). For this reason, web services use the RDF. Three more languages have been developed as extensions to RDFS: OIL, DAML+OIL, and OWL (Martin et al., 2004).

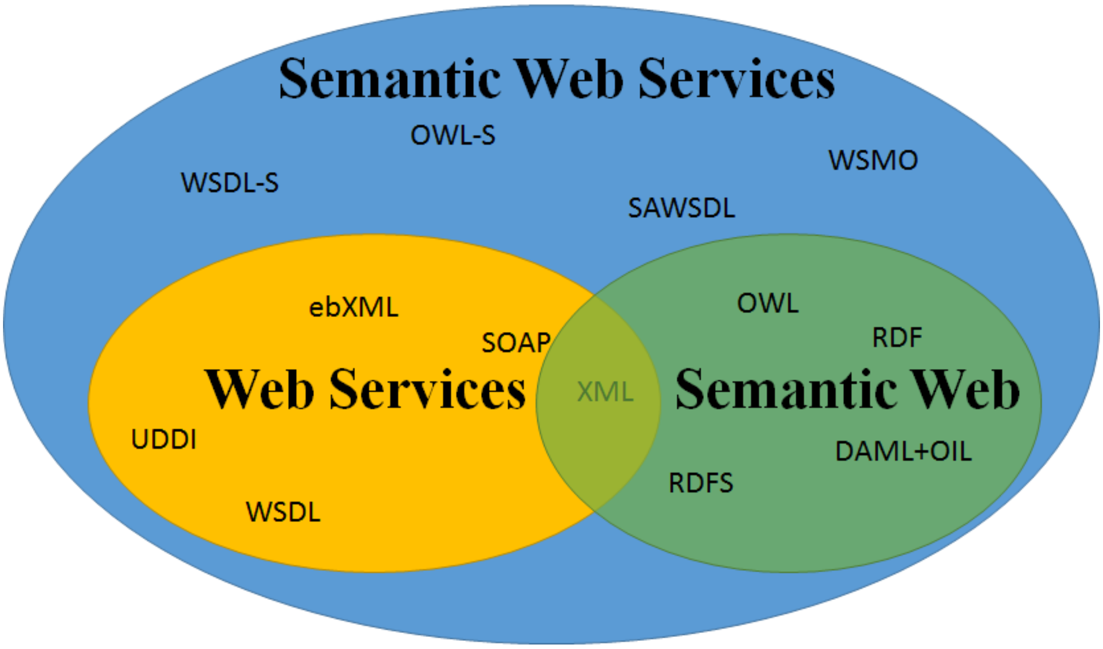

Figure 2.5: Semantic Web service technology

COCOON glue (Della Valle & Cerizza, 2005) is a SW-based Service to integrate complex eHealth services. It used the Web Service Modelling Ontology (WSMO) with an open source f-logic inference engine called Flora2 to run over an open source deductive database system. The WSMO (Roman et al., 2005) is a conceptual model for SW services. It comprises an ontology of core elements for SW services, based on the Web Service Modelling Framework (WSMF), and a Web Service Execution Environment (WSMX). The WSMO is organized around four fundamentals components: Web services, Goals, Ontologies and Mediators, as shown in Figure 2.6:

- Ontologies: define the terminology used by other WSMO elements, regarding concepts, relations, functions, instances, and axioms.
- Goals: describe aspects related to user desires for the requested functionality.
- Web Services: defines the functionalities offered by the service.
- Mediators: it is a link between different WSMO elements to enable interoperability between heterogeneous components.

The grounding ontology is useful for service invocation; it specifies the communication protocols used and the specific service elements such as ports, it provides the link between the description of OWL-S and WSDL specification. Web Service Modelling Language (WSML) is used to formally describe all the elements of the WSMO.

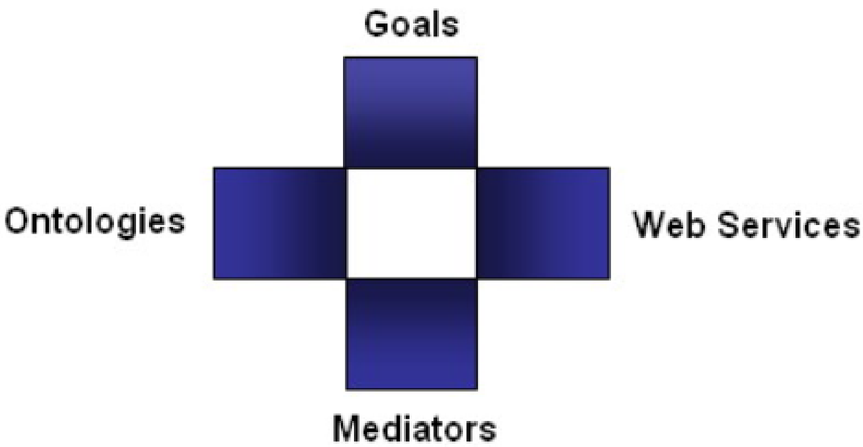

Figure 2.6: The four elements of the WSMO approach

COCOON aims to reduce medical error and develop an efficient Web service management system to publish, discover and compose services. This system has two main advantages; (1) provides a clear separation between the ontologies, and (2) prepares a good performance. The major weakness of this study is related to the use of the f-logic technique for defining similarity metrics. The f-logic is a set of pre-defined rules for making deductions. Methods developed using the f-logic technique are not scalable enough and cannot be applied to a large volume of data.

ARTEMIS (Bicer et al., 2005; Dogac et al., 2006) is a project supported by the European Commission, based on SW Services using the OWL. The structure of this system is similar to COCOON. It aims to describe the semantics of Web service functionality. It also supports the semantic meaning of messages or documents exchanged through Web services. As previously mentioned, using SW technologies not only enables healthcare services to interact with each other easily, but also helps to integrate data across the clinical Web service by using semantic annotations. However, this system does not provide a secure platform for protecting data.

Sonsilphong and Arch-int addressed the interoperability problem in both the domain of data integration and heterogeneous systems. They proposed a SW-based service framework to tackle the problem and generate semantic interoperability among healthcare systems (Sonsilphong & Arch-int, 2013).

Aside from improving healthcare quality, sharing and extracting knowledge in a heterogeneous environment is the most common limitation of CDSSs. Therefore, Zhang, et al. proposed a shareable CDSS that meets this challenge. This system has a SW service framework to identify, access, and leverage independent and reusable knowledge modules located in a central KB. The knowledge modules are defined by an ontological model, terminologies and representation formalisms to support a shareable CDSS. Their contributions consist of representing unified knowledge and patient data in heterogeneous domains, knowledge integration and data interoperation, and semantic development of shareable knowledge for automated KA. This system has been evaluated by two applications including model-level and application-level evaluation. Model-level evaluation confirms coherent knowledge representation. Application-level evaluation validates its high accuracy and completeness. These evaluations show this system is feasible and useful in providing shareable and reusable knowledge for the purpose of diagnosis in decision making. It also offers timesaving benefits and cost effectiveness in comparison with other CDSSs. The system improves the maintainability and scalability of systems to contribute with other CDSSs (Zhang, Gou et al., 2016).

Douali, et al. suggested a SW-based framework to support reasoning to remedy diagnostic errors. The authors believe that diagnostic errors are derived from flawed reasoning, incomplete knowledge, faulty information discovery and inappropriate decision making. This approach contains case-based fuzzy cognitive mapping to support the diagnosis. The framework also evaluates clinical knowledge for decision making through Bayesian belief networks. The reasoning methods for this framework uses a statistical approach to solve diagnosis issues and enhance the efficiency of the system. The reasoning methods used in this approach are implemented through SW tools such as Notation 3/RDF and Euler Sharp inference engine. The strength of this system is its handling of approximate reasoning, incomplete information, control rules for clinical conditions and patient profiling. This approach is in its first stages of development for implementation. It needs to be tested with larger datasets and allow updates of the system to integrate new knowledge (Douali, Csaba, De Roo, Papageorgiou & Jaulent, 2014).

Another study proposed by Wimmer, et al. developed a multi-agent framework called MAPP4MD to provide a privacy preserving mechanism for clinical data in heterogeneous environments. In this study, each agent utilizes ontologies and SW technologies to apply reasoning for a privacy-preserving algorithm. This approach supports data integration and sharing among agents in the various environments for knowledge discovery. The evaluations of this system show that the distributed multi-agent framework is flexible. One the benefits of this approach is to improve data sharing for medical research, population-level analysis, and evaluation at a population-level in healthcare activities. While this framework works well with limited datasets, it needs to be checked against larger datasets to show its scalability (Wimmer, Yoon & Sugumaran, 2016).

Hederman and Khan addressed the problem of standalone CDSSs and a universal CDSS. The authors developed a semi-automated approach to discover, select and compose CDSSs available as Web services. The proposed system is at the elementary level and needs to be implemented and validated. The lack of identifying formalized semantics attached to the services is an obvious challenge for this research (Hederman & Khan, 2012).

SW based CDSSs which improve semantic analysis

The reviewed papers in this section have proposed two SW frameworks to improve semantic analysis. They consist of the Knowledge Engineering (KE) technique and the logic reasoning structure. The main goal of these papers is to improve the KA process in the CDSSs by utilizing SW technologies.

KE technique

Most of the non-SW based CDSSs suffer from a lack of automatic analysis systems. This issue can be addressed by using SW technologies. Any technical and scientific discipline to construct, maintain and reuse knowledge is referred to as a KE technique (Studer, Benjamins & Fensel, 1998). KE is an AI technique that incorporates a huge amount of knowledge, rules and reasoning mechanisms to develop systems such as CDSSs.

Knowledge model construction is one of the most important stages in knowledge engineering in order to model a particular domain for a knowledge-driven system. A knowledge model typically contains three types of knowledge: domain knowledge, inference knowledge, and task knowledge. Modeling knowledge for a specific domain starts with identifying useful sources of model knowledge and then continues with specifying the knowledge model. The model can be through a fully formal language. Finally, the knowledge will be refined by inserting a set of knowledge instances to the knowledge to complete the KB.

There are different types of domain models, such as taxonomies, thesauri, and ontology. Although all of them represent the structure of concepts and relationships in knowledge, the ontology is one of the most formal knowledge representations, establishing knowledge in great detail (concepts, relationships, properties, and values) along with instances of concepts and relationships.

One KE approach was taken in Sanchez, Toro, Carrasco, Bueno et al. (2011) for to help physicians detect early stage Alzheimer's Disease (AD) using multidisciplinary knowledge and reasoning over the underlying KBs. In this paper, researchers used several ontologies (e.g. the MIND ontology, the SW Applications in Neuromedicine (SWAN) ontology, and the SNOMED-CT). Although this project needs to be tested on larger ontological domains, the authors improved the accuracy of results for further decision making processes. In 2012, the system was improved to discover new knowledge and generate new rules for clinical decision making (Toro et al., 2012). Physicians take advantage of this system to help patients discover relevant knowledge for AD diagnosis. This CDSS not only works in the AD domain but also supports other domains such as cancer.

In 2013, Sanchez et al. proposed a more generic software architecture called S-CDSS to solve some of the challenges of CDSSs. They improved the system by adding new tasks to the system such as diagnosis, prognosis, treatment, evolution, and prevention. It helps the system to integrate and reutilise clinical workflow of CDSSs. They stated that discovering new knowledge methods in the previous study ((Toro et al., 2012)) was implicit and they wanted to solve other CDSS challenges. They posited that due to the nature of a system based on a knowledge model provided by a team of domain experts, classical validation is not possible at this stage, and therefore, they assumed that the system is correct. They validated their system by comparing system decisions with end-user decisions.

In another paper, Zhang, et al. developed a model for semantic enhancement of a CDSS by using a KE technique to express the domain of knowledge and the patient data in a unified model (Zhang, Tian, Zhou, Araki & Li, 2016). The architecture include four different phases: (1) KA, (2) knowledge representation, (3) knowledge application, and (4) knowledge evaluation. The main motivations for developing such architectures were to handle multidisciplinary and heterogeneous platforms. The authors claimed that their system proved useful as it could reduce the reduplication of data in the KB. However, it needs to support experience-based reasoning, as well as bridge the gap between a semantic healthcare KB and an existing knowledge representation model.

Another KE approach that aims to improve the performance of CDSS has been proposed by Mohammadhassanzadeh et al. (2016). This approach answers queries by integrating deterministic and plausible knowledge from heterogeneous environments. Researchers in this study used SW technologies to leverage reasoning and extend the coverage of a medical KB. Extending the coverage of medical KBs, by considering potential correlations between decisional attributes is useful, especially when CDSSs need to have complete knowledge for decision making.

There is some rationale for using SW technologies in this approach such as data management, Description Logics (DL)-based inferral methods, and the opportunity to support plausible reasoning. Moreover, using ontology inferencing and conceptual similarity checking improves the accuracy of reasoning in the system. The result of system evaluation shows that this multi-strategy approach improves knowledge coverage of clinical KBs and provides a better diagnostic process for complex diseases. In addition, inferred knowledge can be used in future decision making.

Logic reasoning structure

Bouamrane, et al. proposed a knowledge-based preoperative decision support system to assist health professionals in secondary care in the preoperative assessment of patients before elective surgery (Bouamrane, Rector & Hurrell, 2011). In this system, the authors applied SW technologies such as OWL and logic reasoning to develop an automatic analysis system. The system attaches patient information to the medical context. However, the collected information from patients is still a kind of "coarse-grained" information and needs to be transformed into a "fine-grained" model.

Muthuraman and Sankaran proposed a personalized treatment flow without user intervention (Muthuraman & Sankaran, 2014). The method has been developed using a fuzzy decision tree, fuzzy rules, and SWRL. The advantages of such systems are to provide a user-friendly environment to improve memory performance and to reduce time spent on patient care. The scalability of the proposed model is still under investigation.

Rodríguez-González et al. (2012) suggested a computer-aided diagnostic system called SeDeLo to help experts and non-experts support clinical diagnosis. In this study, the authors developed a CDSS by utilizing SW technologies and DL to diagnose diseases using symptoms, signs and laboratory tests. This system is more efficient and accurate in decision making compared with previous systems proposed by the same authors. Although this method achieves a better result in terms of the accuracy of the system, it is still not scalable enough, and it needs to be developed for the rule description process.

2.6 Knowledge Quality

Figure 2.7 presents a knowledge hierarchy that shows the relationship between data, information, and knowledge. According to Braganza (2004) and Rowley (2007) knowledge is derived from information that is extracted from data. The backbone of knowledge is data. Hence, the quality of knowledge is reliant on data and information quality.

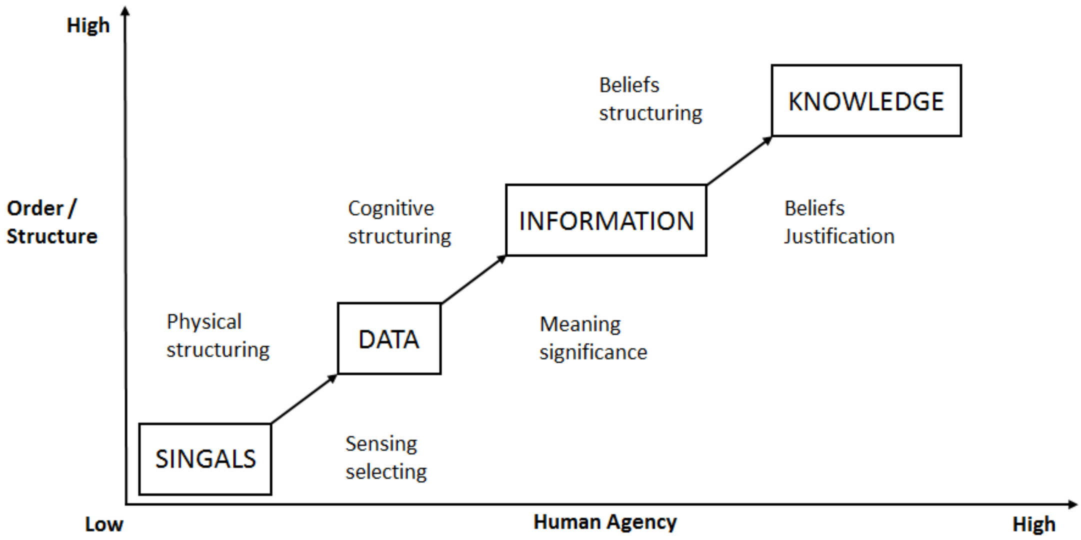

Figure 2.7: The knowledge hierarchy

Knowledge quality is an essential factor for the KM process, solving problems, and decision support. Knowledge QMs can measure KM performance in decision making. Technically, users will not be able to make an intelligent decision when the knowledge quality factors are not high enough for the decision making process. Tongchuay and Praneetpolgrang explain a conceptual framework for ensuring knowledge quality in KM systems (Tongchuay & Praneetpolgrang, 2008). The authors worked on knowledge and knowledge QMs. The paper identified and explained the most important knowledge QMs for assessing knowledge; timeliness, accuracy, completeness, consistency and relevancy. The authors believed that knowledge quality is related to data and information quality, and information QMs can be used to measure the quality of knowledge.

QMs can be used to evaluate the success of a scheme such as an ontology in modeling a real-world domain. The depth, breadth, and height balance of the ontology inheritance tree can play a role in quality assessment. Additionally, the quality of the ontology (i.e., generally a knowledge) can be measured to check whether it is rich and accurate enough to represent real-world entities and relations. More precisely, the quality of the ontology helps to assess how individuals and relationships are well-selected for the ontology.

To this end, Tartir, Arpinar, Moore, Sheth and Aleman-Meza (2005) addressed the problem of determining suitable ontologies for reusing knowledge. The paper proposed a framework called OntoQA to analyze and assess the quality of an ontology. OntoQA is an approach that analyses ontology schemas and their populations (i.e. a KB) and describes them through a well-defined set of QMs. These QMs can highlight the main features of an ontology schema as well as its population. It also enables users to make sound decisions. OntoQA is an interesting study that uses well-defined QMs at schema and instance level of an ontology to measure the quality of knowledge. It is a good method for quality analysis with useful QMs, but, it is limited as to scale, as well as schemas.

In another study, Mostowfi and Fotouhi (2006) offer a schema transformation approach to improve ontology quality. Firstly, the researchers define some criteria with which to analyse quality and then explain transformations with their strengths and weaknesses according to those criteria. They addressed the problem of evolutionary change in a database schema. The paper proposed different schema transformations to work around this issue. The research mentioned some weakness in some works which apply ontology analysis such as OntoQA. They claimed that their proposed method could remedy the issue. The proposed QMs in this paper consist of homogeneity, totality of properties, stability, explicitness, uniformity of properties, size of the ontology, and query simplicity. Homogeneity refers to the level of similarity among individuals of a particular class. Namely, individuals should all have the same set of properties to belong to the class. The totality of properties refers to a total property in a particular domain. The totality of properties is a many-to-one property that covers all the elements of the domain. Ontologies change to reflect new requirements in a particular field of study,so the stability criterion examines how stable the ontology is if change occurs. The explicitness criterion examines the clarity of definitions for classes, properties, relationships and other elements.

Lozano-Tello and Gómez-Pérez (2004) addressed the problem of determining the most appropriate ontologies for answering user queries. They proposed a method to select related ontologies based on proposed QMs. For implementing this method, the authors created a multilevel framework which contains a set of hierarchies to assess the ontologies in depth. These hierarchies have dimensions which demonstrate five aspects: content, language, methodology, tools and cost. This method is based on the Analytic Hierarchy Process (AHP) that assesses hierarchy trees in a step-wise fashion.

Due to the growing popularity of the SW vision, ontologies play a significant role in the representation of knowledge. However, knowledge providers, either a human or an application, could be negatively impacted by creating low quality ontologies. Arpinar, Giriloganathan and Aleman-Meza (2006) addressed the improvement of ontology quality. They have concentrated on the issue of conflicting information as a criterion to improve ontology quality. This paper categorizes different types of conflict and offers a rule-based approach to detect them. This is also a flexible method, and is useful for detecting conflicts. However, this method does not work efficiently in the cases of a large amount of data and rules (i.e., the scalability issue). As a future work, the method needs to be developed for larger scale ontologies.

Interpreting and reasoning with semantics remain significant challenges in KE. Burton-Jones, Storey, Sugumaran and Ahluwalia (2005) proposed some QMs for evaluating the effectiveness of an ontology. The authors used a tool called Ontology Auditor to assess the ontologies of the DAML library. In this paper, the authors considered syntactic, semantic, pragmatic and social QMs for evaluating the quality of ontologies. The main contributions of the research are: (1) it presents comprehensive and theory-based QMs that can support ontology creation and use, (2) it shows how such a QM suite can be implemented in an ontology auditing tool, (3) it demonstrates the usefulness of the QMs by providing empirical evidence of the quality of ontologies.

KM and Learning Management (LM) both serve the same purpose which is to facilitate individuals' learning and competence development, in projects, and in organizations. However, they follow two different perspectives. KM is aligned to an organizational perspective as it addresses the lack of shared knowledge among members of the organization by encouraging individuals to make their knowledge explicit by creating knowledge elements, which can be stored in KBs for later reuse or for participating in communities of practice. LM focuses on the individual perspective, as it concentrates on individual acquisition of new knowledge and the socio-technical means to support this internalization process. The aim of Rech, Decker, Ras, Jedlitschka and Feldmann (2007) was to stimulate the discussion on the meaning of quality in the context of KM. Namely, how knowledge should or should not be described in a particular KM system, and what is needed to generate a fruitful socio-technical KM system. The paper also discusses the meaning of quality of knowledge in the context of KM. It has illustrated knowledge patterns as a knowledge structure in a KM system. The paper showed how to recognize knowledge patterns and knowledge anti-patterns in the KM system. They proposed the knowledge refactoring mechanism to improve or change knowledge anti-patterns and boost knowledge quality.

Table 2.3 shows a brief review of QMs that are utilized for quality assessment in some popular knowledge and ontology models. As seen in the table, the most significant QMs in these models are; accessibility, consistency, interoperability, accuracy, completeness, timeliness, relevancy, relationship richness, class richness, and adoption.

Table 2.3: Standard QMs in some knowledge and ontology quality models

Quality Model	Quality Metrics
Knowledge quality and quality metrics in knowledge management systems (Tongchuay & Praneetpolgrang, 2008)	Accessibility, Consistency, Interoperability, Accuracy, Completeness, Timeliness, Reliability, Relevancy, Believability, Reputation, Understandability, Objectivity, Security, Ease of manipulation, Free of error, Verifiability, Trust
OntoQA: Metric-based ontology quality analysis (Tartir et al., 2005)	Completeness, Relationship Richness, Attribute Richness, Class Richness, Average population, Cohesion, Importance, Connectivity, Readability
Improving quality of Ontology: An ontology transformation approach (Mostowfi & Fotouhi, 2006)	Homogeneity, Totality of properties, Stability, Explicitness, Uniformity of properties, Size of the ontology
Ontology quality by detection of conflicts in metadata (Arpinar et al., 2006)	Consistency, Interoperability, Completeness, Relationship Richness, Class Richness
A semiotic metrics suite for assessing the quality of ontologies (Burton-Jones et al., 2005)	Consistency, Interoperability, Accuracy, Relevancy, Clarity, Comprehensiveness, Lawfulness, Authority, History
The quality of knowledge: Knowledge patterns and knowledge refactorings (Rech et al., 2007)	Interoperability, Adoption, Accuracy, Timeliness, Security, Free of error, Stability, Sustainability, Maturity, Recoverability
Knowledge quality: antecedents and consequence in project teams (Yoo, Vonderembse & Ragu-Nathan, 2011)	Accuracy, Currency, Accessibility, Relevancy, Timeliness, Completeness, Consistency, Credibility, Adaptability, Relationship Richness

2.6.1 QMs used for CDSSs

Table 2.4 represents QMs which have been used in some CDSSs for assessing data and information. These are not about knowledge but data and information so, they cannot completely solve the problem of assessing knowledge quality. As mentioned before, the quality of knowledge is connected to data and information quality, therefore, the KQA approach applies concepts of data and information quality to measure knowledge quality. It modified and improved the data and information QM measurements to assess knowledge quality. They consist of; accessibility, consistency, interoperability, accuracy, completeness, timeliness, relevancy, relationship richness, class richness, security, authority, performance, and usability. In other healthcare systems scalability (Wroe, 2006; Khan et al., 2013), reliability (Khan et al., 2013), similarity (Jensen, Jensen & Brunak, 2012) and maturity (Fayçal & Mohamed, 2011) have also been mentioned, but these are not relevant to CDSSs. These QMs are defined as follows:

Accessibility: Refers to the ability to extract valuable knowledge from KSs. Sometimes extracted knowledge does not contain enough information related ro the user's query.

Consistency: This QM shows to what extent the answer is related to the user query. It means that the extracted knowledge has to be relevant, acceptable and consistent with a query. An inconsistent response has the opposite effect on systems.

Interoperability: In the healthcare domain, interoperability is the ability of different information technology systems to communicate, share, and use the information that has been shared.

Accuracy: The QM used assess extracted knowledge. Accuracy is utilized to check the monolithic relationship between knowledge and the query in CDSSs. It is useful to compare the extracted knowledge from different KSs for a unique query.

Completeness: This QM shows to what degree the extracted knowledge is useful or not useful. The lower value for each class represents the need to extract more knowledge for a class, while the higher value shows the fullness of a class.

Timeliness: This QM indicates the ability of the system to provide a quick response when knowledge is required for treatment. It is an important quality measurement to improve patient care as established by the Institute of Medicine. It is vital for any CDSS because:

- Certain threats occur for patients due to a lack of timeliness in treatment.

- A lack of timeliness in major treatments such as surgery might reduce the quality of treatment.
- A lack of timeliness in diagnosing a condition can result in stress, physical harm and higher treatment costs for patients.

Relevancy: This QM shows to what extend the knowledge contains relevant information to support the user query. The relevancy QM checks the annotations and literal explanations of knowledge and suggests relevant information. It is necessary for every CDSS to verify the relevancy of extracted knowledge to aid making the right decision.

Security: Data security has become especially critical to the healthcare industry due to patient privacy issues.

Relationship richness: This QM represents to what extend the class relationships of the ontology have connectivity among other classes in the ontology.

Class richness: This QM relies on sharing instances among classes of the ontology in oreder to provide rich knowledge.

Authority: This QM aims to organize and evaluate valuable health resources, to prevent duplicate knowledge among resources, and to generate rules and policies for the use of resources. In other words, it helps to evaluate the efficiency of resources for making a decision.

Usability: This QM is the degree to which software can be easily used to answer user needs and requirements.

Table 2.4: Data and information QMs used in some CDSSs

	(De Clercq et al., 2004)	(Hussain et al., 2007)	(Fieschi et al., 2004)	(Trafton et al., 2010)	(Kamaleswaran & McGregor, 2012)	(Testi & Tànfani, 2009)	(Santibáñez et al., 2009)	(Della Valle & Cerizza, 2005)	(Dogac et al., 2006)	(Sartipi et al., 2011)	(Musen et al., 2014)	(D Pierce et al., 2012)	(Sanchez, Toro, Carrasco, Bonachela et al., 2011)	(Hederman & Khan, 2012)	(Huang, Ten Teije & Van Harmelen, 2013)
Accessibility	*			*				*	*		*			*	*
Consistency	*			*		*				*		*			
Interoperability		*						*	*	*	*	*	*	*	*
Accuracy			*				*				*	*	*		
Completeness	*						*					*	*		
Timeliness	*			*	*		*	*	*					*	*
Relevancy			*	*	*			*		*	*			*	
Security										*					
Relationship Richness		*						*			*				
Class Richness		*						*			*				
Authority		*													*
Performance				*		*	*	*			*				
Usability				*									*		

2.7 Knowledge Quality issues for KA for CDSSs

Finding the latest, accurate clinical knowledge to support decision making is difficult. This issue is partly due to the enormous amount of research, guideline data and other knowledge published every year. Recently, there has been exponential growth in the amount of published medical knowledge. For example, PubMed has grown by around 4% a year and contains more than 20 million articles (Lu, 2011). Available KSs are very diverse in terms of formats, structure, and vocabulary. Clinical knowledge may need to be extracted from these diverse locations and sources. In this regard, many biomedical researchers are looking at developing methods to manage and analyze clinical knowledge in this changeable environment (Miller, 1994; Cheung et al., 2009; Sartipi et al., 2011; Yoo et al., 2011).

Since 2005, researchers have been developing SW-based CDSSs to effectively extract knowledge from such heterogeneous environments (Sonsilphong & Arch-int, 2013; Hussain et al., 2007; Wright & Sittig, 2008; Dixon et al., 2013; Minutolo, Esposito & De Pietro, 2012). In the previous sections, we have reviewed and highlighted the KA issues of CDSSs improved by SW technologies. It shows some of the potential approaches to SW technology in supporting CDSSs.

Although SW technologies improve the problem of KA in CDSSs, there are still some issues, which have not yet been considered. For example, in the context of CDSSs, most existing methods do not properly evaluate the quality of extracted knowledge. Here the questions are *"whether the CDSS contains enough knowledge to diagnose a rare condition?"* and *"how to ensure that the knowledge used by CDSS is reliable?"* Conventional search engines cannot comprehensively evaluate whether the knowledge is accurate, reliable and relevant in the case of comorbidities. Inappropriate knowledge can have negative effects on the decision making process. For better decision making, clinicians and practitioners must have confidence in the quality of the knowledge used in CDSSs. The CDSS must evaluate the quality of knowledge that is extracted.

It is vital to provide an appropriate platform for CDSSs and KSs to interact. Every CDSS needs to rely on high quality knowledge retrieved from KSs since the CDSS will not be effective if it uses out-of-date, limited or incomplete knowledge (von Krzysztof Michalik & Kielan, 2013). Providing an intelligent mechanism for communicating between the KBs of CDSSs and KSs is a major concern for today's researchers as inappropriate or low quality knowledge may not provide appropriate outputs. More precisely, the CDSS cannot be effective if it uses irrelevant, incomplete, limited or outdated knowledge in response to a given query about a particular disease or set of symptoms (von Krzysztof Michalik & Kielan, 2013). Hence, there is a need to propose an approach to discover knowledge and check its quality using SW technologies for CDSSs.

2.8 Chapter Summary

The aim of this chapter was to review the literature and background of the basic concepts of CDSSs and SW-based CDSSs. It also briefly explains SW technology. The chapter highlights the potential of using SW technologies for improving KA issues in CDSSs. Recent KA issues for CDSSs improved by SW technologies have been categorized into two main groups; format and data heterogeneity and lack of semantic analysis. The recent related research has been reviewed in this context to highlight the advantage of using SW technologies in the body of current CDSSs.

As discussed, the existing healthcare search engines (i.e., PubMed and Clinical Trials, etc.) do not comprehensively extract and identify high quality knowledge for the CDSSs. The ever-growing amount of clinical knowledge makes the process of extracting high quality knowledge increasingly difficult. None of the reviewed papers have addressed the issue of knowledge quality assessment for CDSSs. In the next chapters, the development of a system to extract, measure, and rank the knowledge quality for CDSSs is explained. Such a system should be able to support a knowledge broker in extracting and ranking knowledge from multiple heterogeneous KSs (i.e. PubMed and other KSs) to keep CDSSs current and support optimal decision making. There is also the possibility of integrating such systems with a precision medicine–based approach (Collins & Varmus, 2015), to allow a CDSS to discover appropriate cases and outcomes that may need to be included in rule revision. **Appendix C** illustrates a brief summary of the literature review covered in this chapter.

Chapter 3

Research Methodology

3.1 Introduction

This chapter covers the research method used in this thesis. It shows the research design of the thesis divided into four steps: (1) Identifying and analyzing the problem, (2) defining objectives, (3) designing and developing the approach, and (4) approach evaluation. This research broadly follows design science research methodology (Peffers, Tuunanen, Rothenberger & Chatterjee, 2007). An outline of the research methodology is shown in Figure 3.1.

As seen in Figure 3.1, the issues and methods of CDSSs have been identified from the literature review. Based on the current issue (i.e., lack of knowledge quality assessment for KA) discovered from related works, the problem statement of this thesis has been identified. After stating the problem, the research questions and objectives have been defined. The candidate knowledge QMs have been applied to the research design. To prove the importance of the knowledge QMs, a questionnaire has been developed and shared among health experts (e.g., practitioners and health informatics scholars) in the Health Informatics New Zealand (HiNZ) and the Australasian College of Health Informatics (ACHI) communities. After identifying QMs approved by health experts, the KQA approach has been developed utilizing SW technologies. Finally, the results achieved with the developed approach have been assessed by health experts to validate the appropriateness of the results. The LR has been continuously considered during each step. Table 3.1 (at the end of the chapter) shows a comprehensive overview of the activities in the steps of this research. This table also shows different tools and methods used in each step. It also indicates different activities of each chapter. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

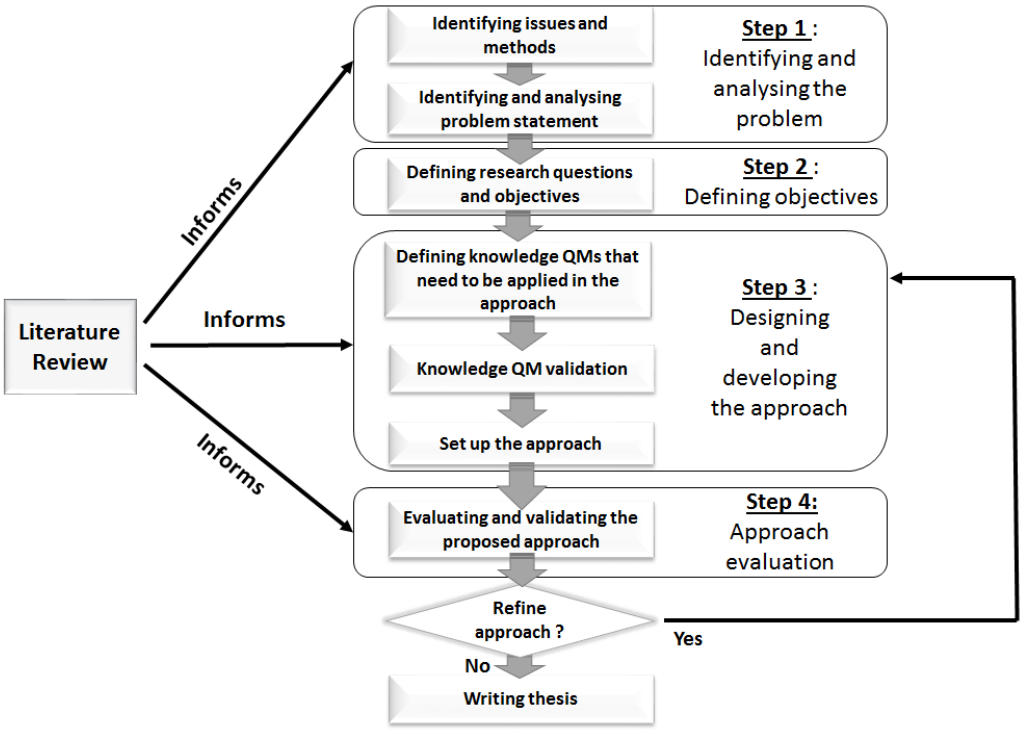

Figure 3.1: Overview of research methodology

3.2 Identifying and analysing the problem

In this step, the addressed issues discovered from the LR are explained. The gap in research has been analysed and defined to formulate the problem statement of this thesis. Aside from explaining the problem statement, the LR has brought forward some methods applied in the CDSSs for the decision making process. These methods help us to identify what kind of tasks have been used for the decision making process and what kind of tasks need to be considered. As seen in Table 3.1, in the first step, relevant studies were extracted using particular keywords such as CDSS, SW technology and QMs. In reviewing the related works, the problem statement (i.e. lack of knowledge quality assessment for KA in CDSS) was defined for the research.

3.3 Defining objectives

The research questions and objectives of this study were defined from the current problem identified from related research. These research questions help to clarify the objectives of this research. The goal is to propose a suitable solutions to tackle the issues mentioned in the research questions.

3.3.1 Formalizing Research Question and Objectives

One of the main concerns of health experts is to gain high quality knowledge to aid the decision making process. In this situation, the main question is "How can knowledge used by CDSS be made reliable and safe?" Obviously, using erroneous knowledge could have negative impacts on patients' health. The following research questions aim to define the KQA approach in discovering knowledge and assessing the quality of that knowledge for KA in CDSSs. The proposed approach takes advantage of SW technologies to remedy the issue. The questions are as follows:

1. What kind of QMs would be useful for assessing the quality of clinical knowledge extracted from knowledge sources?
2. How SW technologies can be used effectively to support CDSSs?

3. Which annotations are useful in improving clinical knowledge for CDSSs using SW technologies?
4. How can QMs be measured to provide high quality clinical knowledge through SW technology?

3.4 Designing and developing the approach

This step is one of the most important parts of this research. The approach was implemented in a small prototype to test its capability but will be expanded to a larger scale in future.

3.4.1 Define knowledge QMs that need to apply in the approach

Before implementing the approach, QMs for KQA have been collected. Candidate knowledge QMs have been collected from the literature for knowledge quality, KB attributes, and data and information QMs used in healthcare systems (refer to Figure 3.2). The candidate knowledge QMs are proposed and clearly explained in Section 5.2.

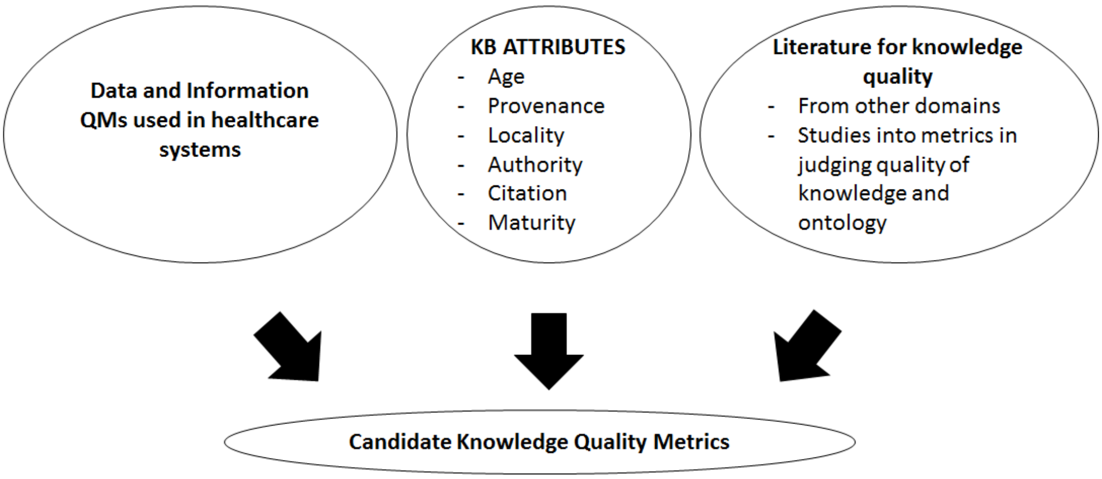

Figure 3.2: Candidate Knowledge QMs

3.4.2 Knowledge QMs validation

To get validation, the candidate knowledge QMs were rated and validated by health experts. A questionnaire was designed and distributed among health experts, and the process of designing and using the questionnaire is explained.

Objectives

The objectives of the questionnaire were twofold. First was to identify those knowledge QMs that are normally used by health experts in the decision making process. The second was to identify the importance of candidate knowledge QMs. The highly rated knowledge QMs were used for the development of the KQA prototype.

Methodology

A focus group approach using a questionnaire given to a convenience sample of health expert were used to validate knowledge QMs. The focus group respondents were health experts in HiNZ and ACHI. A list of rating questions was prepared. The questionnaire was available to all those with access to an online link. If they wished to take part, they could fill in the questionnaire and returned anonymously. They could rate or ignore the candidate knowledge QMs and/or propose important knowledge QMs based on their personal experience.

Participants

Participants were selected from a pool of health experts in the healthcare domain. Participants were contacted via email inviting them to participate. However, due to a low response rate, a snowball sampling methodology was employed to garner further participants. The snowball sampling method consists of using those who have agreed to participate to refer the researcher to others who could be involved. This method can be practical with certain sampling populations, such as those socially isolated, elites, or other hard-to-reach populations (Atkinson & Flint, 2001). A total of ten health experts were recruited in this way.

The pool of health experts targeted were health informatics scholars and practitioners who have some knowledge of CDSSs, who were likely to have to use knowledge that they had not collected themselves or seen before. Demographic data for each health expert was collected after each questionnaire. A form was filled in with data on age, their level of confidence in using CDSSs, and a factor to show how much the health experts think computer-based systems can be useful in human decision making. The rate of confidence in using CDSSs was self-assessed, using a scale from 1 to 10. This factor indicated that most of the participants were confident in using CDSSs. The usefulness of computer-based systems in decision making was assessed on a scale between 1-5 (1: Not at all Important, 2: Slightly Important, 3: Moderately Important, 4: Quite Important, 5: Extremely Important). Section 5.3 shows the results of this questionnaire.

Data Collection

Ethics approval was sought and gained, from Auckland University of Technology Ethics Committee (AUTEC). The application included a participant information sheet, a rating exercise form, four short and long questions, and demographic data. The health expert rated and validated a list of candidate knowledge QMs derived from the LR. These candidate knowledge QMs were data (metadata) that may accompany any clinical knowledge e.g. a knowledge QM that demonstrated the accuracy of the knowledge. The health experts evaluated each knowledge QM and gave a rating on a scale of 1 to 5 where 1 is Not at all Important, 2 is Slightly Important, 3 is Moderately Important, 4 is Quite Important, and 5 is Extremely Important. Copies of the ethics approval and the questionnaire can be found in the Appendix A and Appendix B respectively. The questionnaire was conducted with ten participants as an online questionnaire. Before the online questionnaire , the questionnaire had been distributed to participants at the HiNZ 2015 conference. The response from the HiNZ conference was not enough to reach the questionnaire's goal. To overcome this, the structure of questionnaire was modified to be an online questionnaire and distributed via a link. Fortunately, the results were reasonable.

Limitations

There are some limitations to the questionnaire, the first being the small sample size. as there were few participants, we ran the questionnaire with ten health experts. Therefore, this is not an attempt to demonstrate a definite set of knowledge QMs used by all health experts to determine the quality of clinical knowledge. Rather, it demonstrates that, for a given set of knowledge QMs, this particular group of health experts identified these as important when evaluating the quality of clinical knowledge they are presented with. According to Marshall, Cardon, Poddar and Fontenot (2013), the qualitative research should examine the expectations of their research. In this research, we focused on ten health experts, and we expected that it would be sufficient to ensure the credibility of the approach.

The second possible limitation is the snowball methodology used for recruitment of participants. It could be argued that this does not provide a representative (randomized) sample of health experts. Again, as this is a proof of concept, the thesis is not trying to prove that this is the only way to achieve the goal, but rather that, this is one way of achieving it.

3.4.3 Set up the KQA approach

This section introduces the KQA approach proposed in this thesis. This section explains how a KQA extracts knowledge and assesses the quality of that knowledge to use in

CDSSs. The main mechanism of this approach is to discover and evaluate the quality of extracted knowledge that has been represented in the ontological structures (using SW technologies). This section also explains the advantages of using SW technologies. In the following, KQA system along with its components is briefly explained.

The main goal of a KQA is to improve the quality of KA mechanism in the CDSSs. In this respect, the quality of extracted knowledge will be evaluated before use in the CDSS. Figure 3.3 depicts the interaction of KQA with CDSS. There are five main components for interacting KQA with a CDSS:

1. **User Query:** The user query is given to the KQA as an input.

2. **Patient Data:** Patient data is another type of input data for a CDSS that can be used in the decision making process.

3. **KQA:** The KQA extracts knowledge from various KSs (In this thesis, PubMed was used for the experiments). The KQA aims to discover high quality knowledge based on the proposed knowledge QMs. The KQA extracts knowledge based on a given user query. It then assesses the quality of the knowledge to find the highest quality knowledge for decision-making. The KQA approach takes advantage of SW technologies. The approach assesses the quality of ontological knowledge.

4. **CDSS:** The CDSS helps in the decision making process through receiving patient data and high quality knowledge identified by the KQA.

5. **Supportive outcome:** It is a result of CDSS to help health experts in decision making

As seen in Figure 3.3, there are some differences with the main structure of CDSS shown in Figure 1.1 in Chapter 1. In Figure 3.3, the KQA receives a query and extracts the knowledge based on that query. By applying KQA approach, we separated the entrance of query and patient data. Additionally, KA mechanism is improved by adding quality assessment for the extracted knowledge. When the quality of knowledge is assessed, the high quality knowledge will be selected and sent to the CDSS. The CDSS receives patient data and provide appropriate outcome based on this high quality knowledge to support decision making. This thesis focuses on KQA part to discover the knowledge and assess the quality of that knowledge.

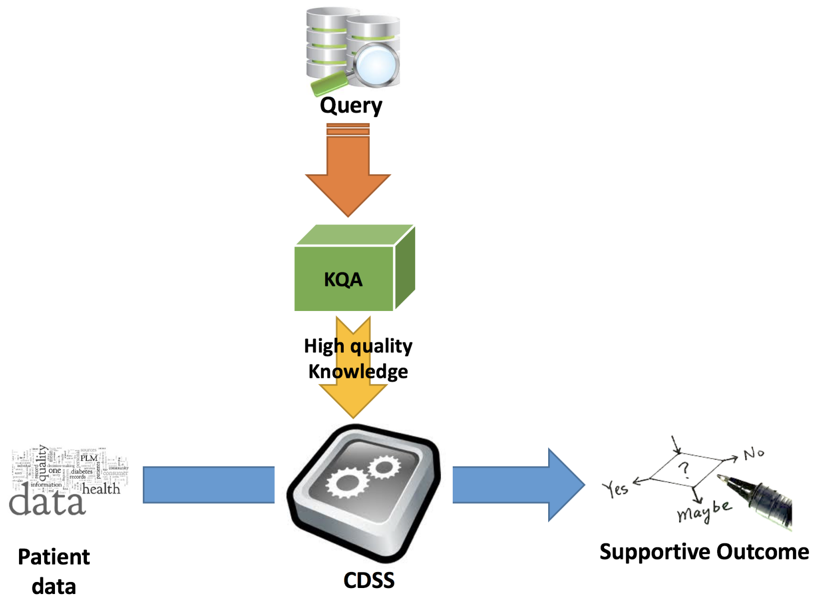

Figure 3.3: The interaction of KQA with CDSS

Benefits of Semantic Web Technologies

The goal of the SW is to represent knowledge on Web pages in machine-readable and human-understandable formats. Ontologies are the backbone of SW. The main purpose of using ontologies is because of their common syntactic and shared semantic levels. Many organizations have now begun to replace old-fashioned ways of storing and sharing data with new human-understandable and machine-readable formats such as RDF that attach semantic specifications to the data. The OWL is a family of knowledge representation languages for ontologies which are builds based on RDF. In this thesis, the KQA transforms the textual knowledge to the ontological structure (via OWL Language) to facilitate the process of evaluating knowledge.

KQA components

The overall framework of a KQA is shown in Figure 3.4. As seen in the figure, the KQA has been built on four main components; Knowledge Discovery, Knowledge Construction, Knowledge Assessment, and Knowledge Delivery.

Each component is briefly explained. Note that the system has a central knowledge repository that stores the updated knowledge along with the query. This stored knowledge has a high quality score. This repository has an ontological structure, and it updates regularly its knowledge based on a query which has been input in the past.

Knowledge Discovery

When the KQA first receives a user query, it checks the query against the central repository to check for the presence of any similar query already in the repository. In the case of a former query being present, the KQA does not need to extract any new knowledge. It only needs to deliver the stored knowledge to the CDSS.

In cases where the repository does not have the results to any similar query, the KQA starts to extract related knowledge from the KSs (e.g., PubMed). The extracted knowledge will then be sent to the Knowledge Construction component to be transformed into the ontological structure. The process of extracting knowledge from PubMed (i.e., the Knowledge source) is discussed in Chapter 4, Section 4.2.

Knowledge Construction

This component is responsible for transforming textual knowledge into the ontological structure. This task is completed using SW technologies (i.e. OWL language) with Protégé Ontology Editor plugin for Eclipse. Various APIs and Java programming have been employed to help create the ontological structures. The extracted concepts will be added to the ontology as new annotations. The process of creating an ontological structure is discussed in Chapter 4, Section 4.4.

Knowledge Assessment

This component assesses the quality of ontological knowledge use in the CDSSs. As mentioned in Section 3.4.2, health experts will choose from the candidate knowledge QMs for evaluating the quality of knowledge. Section 5.2 lays out in detail the candidate knowledge QMs used in this scenario. In this process, a Knowledge Quality Indicator (KQI) is given to the extracted knowledge. The KQI will be used to rank the evaluated knowledge. The KQI expresses the quality of the assessed knowledge.

Knowledge Delivery

In this component, high quality knowledge will be delivered to the CDSSs to facilitate health experts' decision making. As mentioned earlier, the evaluated knowledge along with the query that discovered it will be stored in the central knowledge repository for further use.

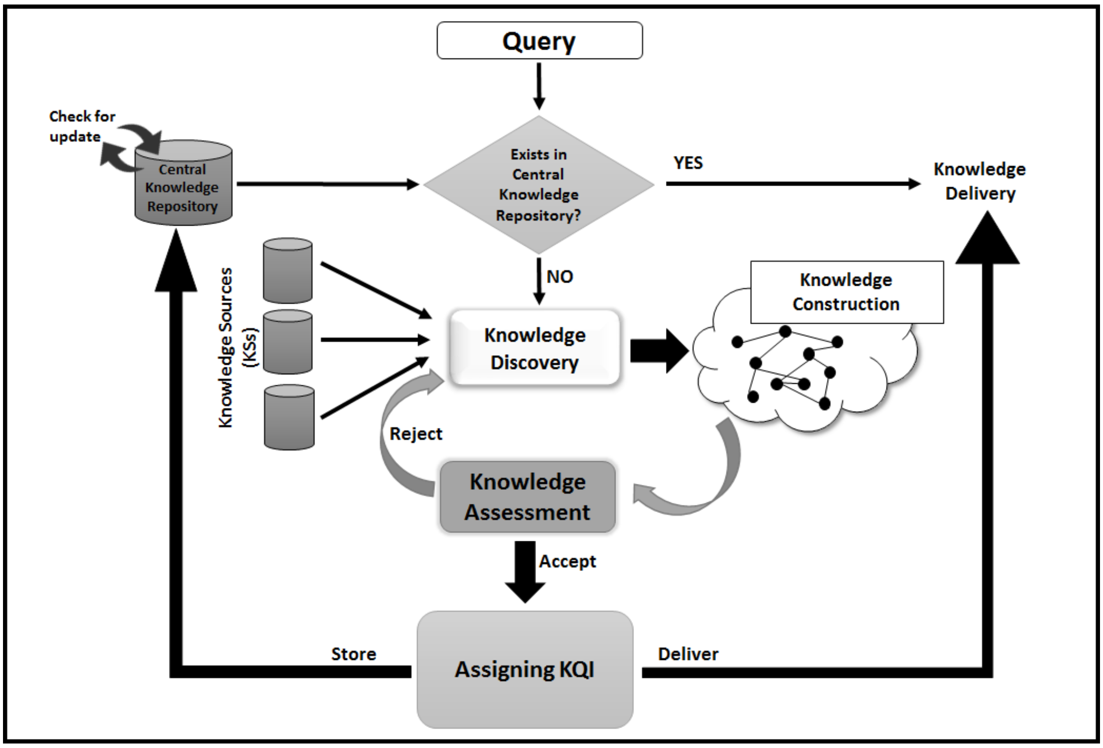

Figure 3.4: KQA framework

Designing and implementing the User Interface (UI)

The UI provides an environment in which a user enters target keywords and knowledge attributes into the KQA. This UI has seven main components that facilitate the process of entering and refining user queries. Figure 3.5 shows the interface implemented in this work.

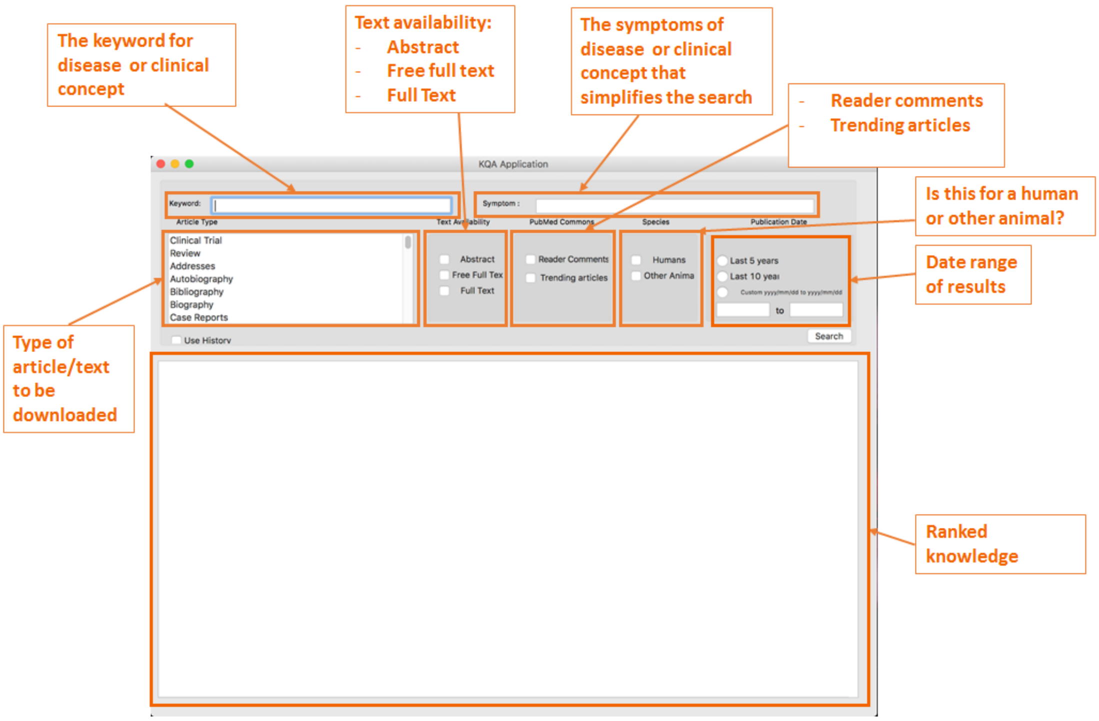

Figure 3.5: KQA UI

The keyword is a component that can be used to receive the name of a disease or condition or a particular medical topic. The knowledge used in clinical KSs are usually in textual or document format. The article type facilitates the process of selecting a particular type of document. This interface allows the user to extract the abstract or the full text of the knowledge item. This UI also provides the capability to search the human beings or animal domain. Knowledge items published in stipulated periods can also be extractable through this interface. The interface also stores the retrieved results in a separate history file. Note that the evaluated and ranked knowledge will be represented in the text area of the interface.

3.5 Approach evaluation

Evaluation is an important step as it proves that the proposed approach is effective enough to be used in a real-world scenario . This study contains two types of evaluation, one related to the validation of knowledge QMs, the other is evaluating the approach. Knowledge QM validation is an in-process evaluation for this research (Refer to Section 3.4.2). Here, health experts decide how important the knowledge QMs are for decision making.Evaluation of the approach is also evaluating this research. It demonstrates the performance of the proposed approach. In this part, knowledge items were given to health experts to rank by quality, based on their experience via an on-line questionnaire (See Appendix D). The results will be checked against the outcome of the KQA approach to compare the efficiency of the designed approach. The knowledge items used in the KQA approach are the same as the knowledge items ranked by the experts.

3.6 Chapter Summary

This chapter gives an overview of the research methods used in thesis. The aim of the research is highlighted through a main problem statement along with the research questions. The steps used in the thesis have been introduced, and the process of developing each step is also clarified. The candidate knowledge QMs are identified from related work to improve assessment of knowledge quality in CDSSs. By running a questionnaire, the candidate knowledge QMs are reviewed and assessed by health experts. The overall framework of the KQA along with its components have been introduced. The process of evaluating and validating the approach is discussed in Chapters 6 and 7.

Table 3.1: A comprehensive overview of activities in each step of this research

Step	Activities	Methods / tools used	Related Chapter / Section
Step 1	***I. Identifying issues***		
	a) Reviewing articles and books, related to health informatics, healthcare systems, and clinical KBs	LR	Chapter 1 and 2
	b) Reviewing literature about CDSSs as one of the main keywords and concepts in this research	LR	Chapter 2, Section 2.2
	c) Reviewing the KA issues addressed in CDSSs	LR	Chapter 2, Sections 2.4 , 2.5
	II. Identifying methods used		
	a) Reviewing methods used in CDSSs	LR	Chapter 2, Section 2.3
	b) Reviewing the literature about SW technology (as a recent technology used in CDSSs	LR	Chapter 2, Section 2.5.1
	c) Reviewing the literature as to how SW technology solves the CDSS issues	LR	Chapter 2, Section 2.5.2, 2.5.3
	III. Identifying and analysing the problem		
	a) Defining the problem statement by reviewing the literature	LR, inductive and deductive reasoning	Chapter 2, Section 2.7
Step 2	***I. Defining research questions and objectives***		
	a) Formalizing research questions and objectives extracted from problem statement	Inductive and deductive reasoning	Chapter 3, Section 3.3.1
Step 3	***I. Defining knowledge QMs that need to be applied in the approach***		
	a) Reviewing studies on knowledge quality	LR	Chapter 2, Section 2.6
	b) Identifying knowledge QMs used for CDSSs	LR	Chapter 2, Section 2.6.1
	c) Defining candidate knowledge QMs to use in quality assessment system	LR, Inductive and deductive reasoning	Chapter 5, Section 5.2; Chapter 3, Section 3.4.1
	II. Knowledge QM validation		
	a) Designing a questionnaire to validate knowledge QMs	Questionnaire	Chapter 3, Section 3.4.2
	b) Rating and validating knowledge QMs using questionnaire	Questionnaire, averaging the Likert scale and creating a ranked list of knowledge QMs	Chapter 5, Section 5.3
	III. Set up the approach		
	a) Designing KQA framework to discover knowledge and assess knowledge quality		Chapter 3, Section 3.4.3

	b) Defining and implementing knowledge discovery component • Extracting knowledge from knowledge sources • Extracting concepts from knowledge to create ontologies	Java programming language, Entrez eutils (PubMed API), Google API, XML Parser, Text Mining technique, SW technologies, NLP	Chapter 4, Sections 4.2 and 4.3
	c) Constructing ontologies of extracted knowledge • Matching extracted concepts with UMLS and SNOMED-CT • Building ontologies based on extracted concepts • Defining knowledge QMs measurements to use in the approach • Implementing a prototype of the KQA	Concept matching and mapping, UMLS, SNOMED-CT browser, Text Mining technique, SW technology(e.g. Ontology creation, ontology matching and comparison), Protégé, Java programming, Eclipse, OWL API, Jena library, XML parser, NLP	Chapter 4, Sections 4.3 and 4.4.2; Chapter 5, Section 5.4; Explanation of KQA in Chapter 3, Section 3.4, Codes in attached digital Appendix
Step 4	***I. Approach evaluation*** a) Evaluating results through using a sample of real-world knowledge b) Discussing whether the results and approach implementation can work effectively		 Chapter 6 Chapter 7, Sections 7.1 and 7.2

Chapter 4

Knowledge Discovery And Knowledge Construction

4.1 Introduction

This chapter explains the process of extracting and generating knowledge in an ontological structure using SW technologies. As previously mentioned in this thesis, textual knowledge extracted from KSs have been transformed into an ontological structure to facilitate the process of knowledge evaluation by machines.

Section 4.2 illustrates different processes of extracting and discovering knowledge and Section 4.3 discusses different concepts used in an ontological structure. Finally, Section 4.4 explains the process of constructing ontological knowledge in detail. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

Figure 4.1 shows a broad outline of how KQA works in knowledge discovery and knowledge construction. As seen in this figure, a query has been received by the KQA UI and sent to the KQA. The KQA extracts the knowledge from PubMed and Google scholar KSs by Entrez eutils (for PubMed) and Google Scholar APIs. The extracted knowledge is in the XML format. The extracted knowledge is then sent to the concept and context extraction component which is a part of the knowledge discovery process. This part helps the KQA to extract the concepts used in the knowledge item. In this part, the concepts which are required for constructing an ontology of knowledge will be extracted utilizing Natural Language Processing (NLP), text mining, XML parsing, and SW technologies. The extracted concepts will be checked against SNOMED-CT and UMLS to enrich the knowledge. Finally, the extracted concepts will be sent to knowledge construction component to construct an ontological knowledge structure. The knowledge construction part uses OWL API, Protégé Ontology Editor, and Java programming. At the end, the knowledge ontologies will be recorded in the central knowledge repository to be used in the knowledge assessment component to assess the quality of the knowledge.

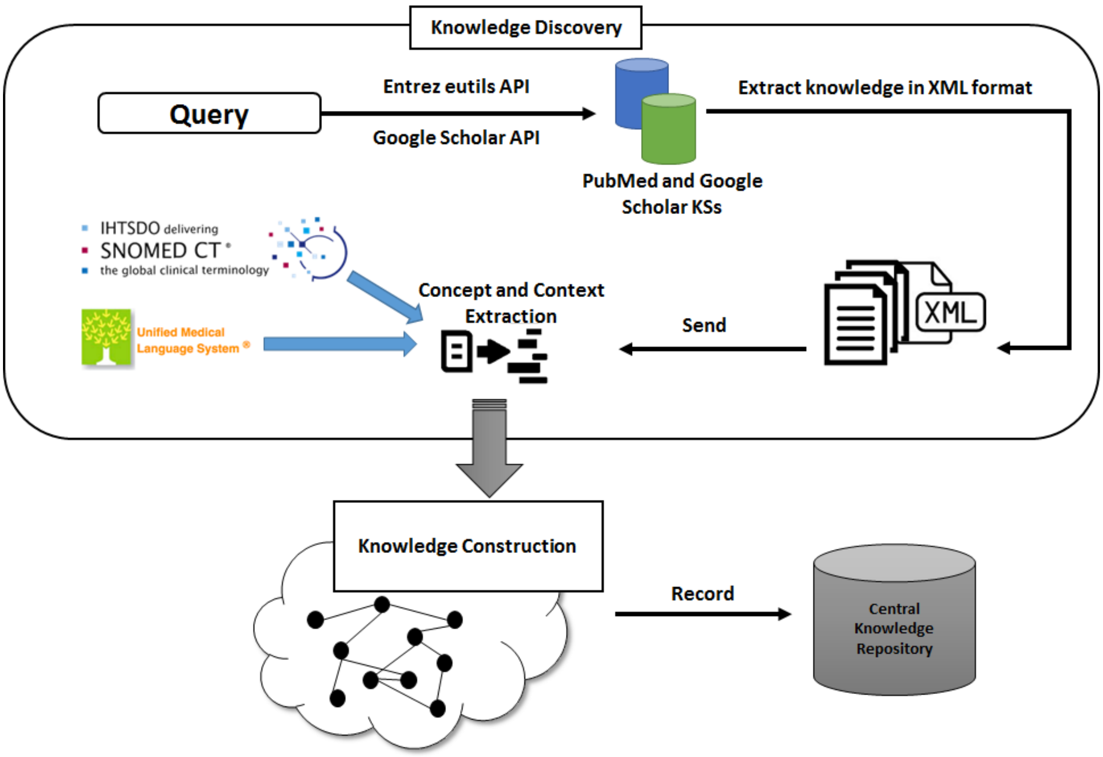

Figure 4.1: Knowledge Discovery and Knowledge Construction workflow in the KQA

4.2 Knowledge Discovery

4.2.1 Extracting knowledge from PubMed

This section explains the process of extracting knowledge from the PubMed KS. For this, the Entrez eutils API was used to extract knowledge based on a given query. Note that all of these processes were implemented using the JAVA language. The following link is used to implement the process of knowledge discovery with Entrez eutils.

https://eutils.ncbi.nlm.nih.gov/entrez/eutils/esearch.fcgi?

The "**HttpsURLConnection**" Java library provides a proper connection between the Entrez eutils API and the system (i.e., KQA). For example, the following command can be used to extract knowledge related to "Tuberculosis Arthritis":

https://eutils.ncbi.nlm.nih.gov/entrez/eutils/esearch.fcgi?db=pubmed&term=(tuberculosis arthritis%5BTitle/Abstract%5D)+AND+English%5Blanguage%5D

In the above command, the query placed after the "?" sing. "db=..." indicates which database contains the knowledge related to a query. The "term=..." indicates the keyword used in the query that can be applied to extract knowledge from PubMed. In order to refine the query, extra information can be added to the end of the command. In this example, the command shows that the extracted knowledge needs to be in English (English%5Blanguage%5D). The domain of knowledge can be related to humans or animals. The "%5B" and "%5D" are ASCII codes which represent "[" and "]." This part of the implementation helps to facilitate a refined query for extracting related knowledge from the KS.

After applying the above commands, the Entrez API returns the IDs of extracted knowledge as an XML format file. Figure 4.2 shows a sample of the XML file for the given query. As seen in the figure, the ID tags of the extracted knowledge are given. Here a method has been developed to read the IDs and store them in the database. After storing the IDs, the **efetch** command (which is defined in the Entrez eutils API) helps to extract the related knowledge based on the given IDs. This command can be executed using the following link:

https://eutils.ncbi.nlm.nih.gov/entrez/eutils/efetch.fcgi?fetch term

Rather than using the “fetch term” in the above command, it is also possible to use a related statement to extract related knowledge. This statement contains different information including the IDs of the related knowledge items, the database name, the software name, the programming language, and the user’s name. For example, the following command can be used to extract the related knowledge shown in Figure 4.2:

https://eutils.ncbi.nlm.nih.gov/entrez/eutils/efetch.fcgi?db=pubmed&id=25328618, 24509226, ...,6606156&retmode=xml&tool=javaEclipse&email=... @aut.ac.nz

In the above command which is a kind of efetch command, the written statement before “?” is the same for all efetch commands. The statement after “?” can be used to extract related knowledge. In the above command, the “db=...” shows the type of database, “id=...” indicates the IDs of knowledge item and the “retmode=xml” indicates the format of the extracted results (Here the extracted format is an XML). To avoid being blocked by the Entrez API, it is necessary to give information related to the software and the user’s e-mail address or company address to the API. In this respect, in the above command, “tool=javaEclipse” shows the software which is Eclipse and “email=...” indicates the user’s e-mail address. Through running this command, the API delivers a particular XML file to the system. This file contains the published knowledge items in the KS. The Entrez API saves all knowledge in a comprehensive tag called PubMed ArticleSet. Each knowledge item has been linked to a particular tag called PubMedArticle. Different information related to a particular knowledge item has been stored with different types of tags. For example, the “Date Created” shows the date of creation in PubMed, the “Article Title” represents the title of the knowledge item, the “Abstract Text” shows a summary of the knowledge, and the “MeshHeadingList” shows all MeSH terms used in the knowledge item. Figure 4.3 presents a fragment of the XML file showing different types of tags. The completed version of this file can be found on the digital Appendix of the thesis. After receiving the XML file, the system extracts the relevant information from the extracted knowledge item using an XML parser.

4.2.2 Extracting knowledge citations from Google Scholar API

Google Scholar API was employed to extract citations of the knowledge items extracted from PubMed. Figure 4.4 shows a small part of Google Scholar API (which is written in Java) that can be used to extract the information related to citations. In order to create a connection between KQA and Google Scholar API, a https link was used. This link was built from two main parts split by “?”. The static part of this link is “http://scholar.google.com/scholar?”. After the “?” sign, the main part of the query can be added to the link. For example, the following link shows how to extract details (including citations) on a knowledge item with the title of “Tuberculosis arthritis of the metatarsal phalangeal: a rare location.”

http://scholar.google.com/scholar?hl=en&q=Tuberculosis+arthritis+of+the +metatarsal+phalangeal%3A+a+rare+location

In the rest of the thesis PubMed was used rather than Google scholar as KS.

```xml
<?xml version="1.0" encoding="UTF-8" ?>
<!DOCTYPE eSearchResult PUBLIC "-//NLM//DTD esearch 20060628//EN"
"https://eutils.ncbi.nlm.nih.gov/eutils/dtd/20060628/esearch.dtd">
<eSearchResult>
  <Count>18</Count>
  <RetMax>18</RetMax>
  <RetStart>0</RetStart>
  <IdList>
     <Id>25328618</Id>
    <Id>24509226</Id>
    <Id>22081281</Id>
    <Id>21881984</Id>
    <Id>21597950</Id>
    <Id>20517730</Id>
    <Id>20303766</Id>
    <Id>19784661</Id>
    <Id>18514528</Id>
    <Id>17344697</Id>
    <Id>16906073</Id>
    <Id>12920652</Id>
    <Id>12685934</Id>
    <Id>9002033</Id>
    <Id>10707734</Id>
    <Id>8014942</Id>
    <Id>3630669</Id>
    <Id>6606156</Id>
  </IdList>
  <TranslationSet/><TranslationStack>
    <TermSet>
      <Term>tuberculosis arthritis[Title/Abstract]</Term>
      <Field>Title/Abstract</Field>
       <Count>24</Count>
       <Explode>N</Explode>
     </TermSet>
     <TermSet>
       <Term>English[Language]</Term>
       <Field>Language</Field>
       <Count>22356377</Count>
       <Explode>N</Explode>
    </TermSet>
    <OP>AND</OP>
  </TranslationStack>
  <QueryTranslation>tuberculosis arthritis[Title/Abstract] AND English[Language]</QueryTranslation>
</eSearchResult>
```


Figure 4.2: esearch results from the Entrez eutils API

```xml
<!DOCTYPE PubmedArticleSet PUBLIC "-//NLM//DTD PubMedArticle, …….">
<PubmedArticleSet>
<PubmedArticle>
  <MedlineCitation Status="MEDLINE" Owner="NLM">
    <PMID Version="1">25328618</PMID>
    <DateCreated> …… </DateCreated>
    <Article PubModel="Electronic-eCollection">
      <Journal>
        <ISSN IssnType="Electronic">1937-8688</ISSN>
        <JournalIssue CitedMedium="Internet">
          <Volume>17</Volume>
          <PubDate>
            <Year>2014</Year>
          </PubDate>
        </JournalIssue>
        <Title>The Pan African medical journal</Title>
        <ISOAbbreviation>Pan Afr Med J</ISOAbbreviation>
      </Journal>
      <ArticleTitle> …………….</ArticleTitle>
      <Pagination>
        <MedlinePgn>323</MedlinePgn>
      </Pagination>
      <ELocationID EIdType="doi" ValidYN="Y">10.11604/pamj.2014.17.323.4220</ELocationID>
      <Abstract>
        <AbstractText>…...</AbstractText>
      </Abstract>
      <AuthorList CompleteYN="Y">
        <Author ValidYN="Y">
          <LastName>Berrady</LastName>
          <ForeName>Mohamed Ali</ForeName>
          <Initials>MA</Initials>
          <AffiliationInfo>
            <Affiliation>…… , Morocco.</Affiliation>
          </AffiliationInfo>
        </Author>….
         ……
         …….
      </AuthorList>
      <Language>eng</Language>
      <PublicationTypeList>
        <PublicationType UI="D002363">Case Reports</PublicationType>
        <PublicationType UI="D016428">Journal Article</PublicationType>
      </PublicationTypeList>
      <ArticleDate DateType="Electronic">
        <Year>2014</Year>
        <Month>04</Month>
        <Day>29</Day>
      </ArticleDate>
    </Article>
    <MedlineJournalInfo>… </MedlineJournalInfo>
    <ChemicalList>…    </ ChemicalList >
    <CommentsCorrectionsList>…</CommentsCorrectionsList>
    <MeshHeadingList>
      <MeshHeading>
        <DescriptorName UI="D000995" MajorTopicYN="N">Antitubercular Agents</DescriptorName>
        <QualifierName UI="Q000627" MajorTopicYN="N">therapeutic use</QualifierName>
      </MeshHeading>
         ….
         …..
    </MeshHeadingList>
    <OtherID Source="NLM">PMC4198287</OtherID>
    <KeywordList Owner="NOTNLM">… </KeywordList>
  </MedlineCitation>
  <PubmedData>
    <History> ... </History>
    <PublicationStatus>epublish</PublicationStatus>
    <ArticleIdList>
      <ArticleId IdType="pubmed">25328618</ArticleId>
      …..
    </ArticleIdList>
  </PubmedData>
</PubmedArticle>
…….
</PubmedArticleSet>
```


Figure 4.3: A fragment of eftech results from the Entrez eutils API

```
public Table getRecordsByUrl(String url) throws IOException {
                MemoryTable records = new MemoryTable("scholar", new String[] {
                                "title", "url", "year", "doi", "origin", "cites", "citeid",
                                "infoid", "britid" });
        Document doc = getDocument(url);
        outer: for (;;) {
          Elements elements = doc.select("div.gs_r");
            for (Element element : elements) {
                Record record = records.createRecord();
                Elements links = element.select(".gs_rt a[href]");
                if (links.size() >= 2)  throw new IllegalArgumentException("Too many article links in scholar record");
                else if (links.size() == 1) {
                    record.setValue("url", links.first().attr("href"));
                    record.setValue("title", links.first().text());
                } else {
                    String title = element.select(".gs_rt").text();
                    if (!title.startsWith("[CITATION]"))
                        throw new IllegalArgumentException("Unexpected title format for scholar record");
                    title = title.substring(10).trim();
                    record.setValue("title", title);
                }
                links = element.select("span.gs_a");
                if (links.size() != 1) throw new IllegalArgumentException("No summary line in scholar record");
                else {
                    String origin = links.first().text();
                    record.setValue("origin", origin);
                    Matcher matcher = yearPattern.matcher(origin);
                    if (matcher.find())
                        record.setValue("year", matcher.group(1));
                }
                record.setValue("cites", "0");
                links = element.select(".gs_fl a[href]");
                for (Element link : links) {
                    String text = link.text();
                    if (text.startsWith("Cited by ")) {
                        Matcher matcher = citeidPattern.matcher(link.attr("href"));
                        if (!matcher.find()) throw new IllegalArgumentException("Cites url does not contain the cites field");
                         record.setValue("citeid", matcher.group(1));
                         record.setValue("cites", text.substring(9));
                     } else if (text.startsWith("Find it")) {
                          Matcher matcher = doiPattern.matcher(link.attr("href"));
                          if (matcher.find())
                                record.setValue("doi", matcher.group(1));
                     } else if (text.equals("Import into BibTeX")) {
                                Matcher matcher = infoidPattern.matcher(link.attr("href"));
                                if (!matcher.find())  throw new IllegalArgumentException("BibTex url does not contain the info
                                                                                                  field");
                                record.setValue("infoid", matcher.group(1));
                      } else if (text.equals("BL Direct")) {
                                Matcher matcher = britidPattern.matcher(link.attr("href"));
                                if (!matcher.find()) throw new IllegalArgumentException("BL Direct url is not well formatted");
                                record.setValue("britid", matcher.group(1));
                      }
                }
                records.addRecord(record);
        }
                                …………..
                                ……………
}
```

Figure 4.4: A fragment of Google Scholar API code for extracting citation of knowledge

4.3 Extracting related information for creating ontologies

As mentioned previously in Section 3.4.3, the KQA has been developed by utilizing SW technologies. SW-based applications facilitate the process of knowledge modelling and knowledge creation. They also provide machine understandable methods for analysis. In the context of the healthcare domain, many ontologies have been created. One of most the well-known healthcare ontologies is UMLS.

UMLS is a comprehensive repository of medical concepts and relationships among concepts. It uses different languages and disciplines by combining more than 100 medical vocabularies. This ontology describes relationships between medical concepts and it represents them as a semantic network of broad category types. Although UMLS provides a great deal of detail about diseases, it does not incorporate relations between diseases and their causes.

This section explains how a domain-specific ontology has been created from a medical text utilizing NLP techniques. The extracted relationships between medical concepts are used to create a semantic network of medical terms and relationships for a particular domain. This network has been linked to the UMLS network by a concept matcher to extract similar concepts. These concepts have been identified by applying lexical and conceptual metrics. It is essential to note that to create the hierarchical structure of concepts (i.e., A concept used in the ontology is considered a class) the SNOMED-CT browser has been used alongside UMLS. The advantage of such an approach is that it uses the domain data to build manageable domain-specific ontologies. These ontologies can be directly used for different knowledge processing purposes. There has been some research that aims to convert textual data to ontological structure such as TextToOnto (Cimiano & Völker, 2005), OntoLT (Mukherjea & Sahay, 2006), and OntoLearn (Navigli & Velardi, 2004). The TextToOnto is an intelligent framework for ontology creation from textual sources. Many data mining techniques have been implemented in TextToOnto. Clustering techniques, pattern based matchers and WordNet dictionary matching are used for the process of extracting knowledge in TextToOnto. Association Rule Mining (ARM) and named relation subcategorization are used for the process of extracting relations. OntoLT is another system that manually defines mapping rules for extracting relations. OntoLearn also introduces some algorithms for interpreting semantic relations utilising WordNet and a sense disambiguation algorithm. Many knowledge engineering-based approaches have used Protégé (i.e., an ontology editor) to model the domain-specific ontologies.

The KQA was developed based on dictionary matching utilising UMLS and WordNet. The KQA also uses relational relearning based on general SPO $(Subject, Predicate, Object)$ patterns. Here, the $Predicate$ is the verb that links $Subject$ to $Object$.

4.3.1 Extracting Concepts and Contexts

As mentioned in Section 4.1, the PubMed API and Google Scholar API have been applied to extract related knowledge in XML format. The KQA receives the knowledge items. It then maps useful statements used in the abstracts of knowledge to the concept identifier and semantic types mentioned in the UMLS. All of these processes have been conducted using the MMTx Application (Osborne, Lin, Zhu & Kibbe, 2007).

The MMTx is a JAVA re-implementation of MetaMap for biomedical researchers in a genetic configurable environment. The MetaMap maps text to the concepts in the UMLS Metathesaurus. It is also capable of detecting Metathesaurus concepts in the textual documents. The MetaMap passes the texts to a series of modules. More technically, the texts is passed into different components such as sentences, paragraphs, phrases, lexical elements and tokens. Variants are generated from the resulting phrases. The selected concepts from the UMLS Metathesaurus are assessed against the phrases.

Finally, the best candidates are collected into a final mapping.

The MMTx application has several advantages, being; it is machine-portable, through using the JAVA language, modular, re-useable, maintainable and configurable; However, it will not be able to provide the same result as original MetaMap. It is used in this work as KQA is based on JAVA language.

Furthermore, the hierarchical structure of classes in the ontology can be represented better using SNOMED-CT. Additionally, the KQA uses the MeshHeadings used in the XML file to create classes in the ontology. MeSH is a comprehensive controlled vocabulary for the purpose of indexing journal articles and books in the life sciences. The MeSH terms are only available through PubMed knowledge source. If the knowledge extract from the other knowledge sources, the UMLS concept matcher will help the system to find the relevant classes for the ontology.

The KQA needs to construct a context map of related terms used in the domain. This task has been completed using the MedPost SKR Tagger that is employed to extract Noun Phrases, and Verb Phrases (i.e., triple pattern) used in the title, abstracts, and MeshTerms (Smith, Rindflesch, Wilbur et al., 2004). Approximate matching such as permutations of words in the retrieved phrases are also employed to seek the synonyms and abbreviations to match with the domain terminology used in the UMLS. A higher weight is given to terms occurring in titles than to terms occurring elsewhere. A stopword list used in the SMART system (Buckley, 1985) is applied to ignore non-informative words from the retrieved phrases. Moreover, term frequencies are considered for ranking phrases. Finally, a list of ranked phrases is constructed. In order to build a comprehensive ontology, it is necessary to assign the best matching concept identifier to the phrases.

4.3.2 The Process of Concept matcher

Semantic Match

In this step the best matching concepts have been selected and assigned to the domain phrase. The text map is used to discover a conceptual match between phrases and concepts. Note that these phrases can map to a particular UMLS concept or multiple concepts. In this step, the KQA considers the related phrases with exclusive mapping concepts. It then constructs a suffix tree for the hierarchical concepts to calculate the conceptual distance between two concepts. This task has been done by spreading an activation search over the UMLS hierarchical structure. It is important to note that there exist many common concepts between two given concepts. In this scenario, the shortest path to a common concept links the closet matching concepts. The KQA considers the fact that the related terms in the context map are closely related to each other in the UMLS hierarchical structure.

Lexical Match

It might not be possible to discover a semantic match between concepts in the UMLS. UMLS has a term called Concept Unique Identifiers (CUI). Every individual concept in UMLS has its own CUI. There exist links such as “broader” or “narrower” in the UMLS Matathesaurus that are not well defined, as they usually reference related terms from different vocabularies. Based on this observation, the KQA used a lexical matcher using the Edit Distance (ED) mechanism to identify the concepts that match best to create classes. The ED algorithm has been explained in Algorithm 2 of Chapter 5.

4.3.3 Relationship Matcher Process

Sometimes users are interested in certain types of relationships. Therefore, it is vital to allocate proper types to the discovered verbs in the relationship triple (i.e., spo). The patterns have been constructed for UMLS semantic network relationships. These groups were assigned to the retrieved verbs (i.e. predicates). To increase the accuracy of this process, the WordNet dictionary resources were used to discover word sense synonyms for verbs to match against the patterns.

4.4 Knowledge construction

This section explains the process of constructing knowledge using information collected from the previous sections. The constructed knowledge is in an ontological structure. In Chapter 2, the background knowledge related to ontology and OWL have been discussed in detail.

4.4.1 Ontology Components

An OWL ontology contains three main components called individuals, properties, and classes. The following explains each component in detail.

Individuals

Individuals shows entities in the domain of interest. They are also known as instances of an ontology. They are something that the ontology describes. Individuals might model concrete entities such as proteins or organizations. They might also model very abstract entities such as an article or a particular drug. Technically, individuals are a very formal component of an ontology. Figure 4.5 represents some individuals of different domains. In this figure, individuals are shown as diamonds.

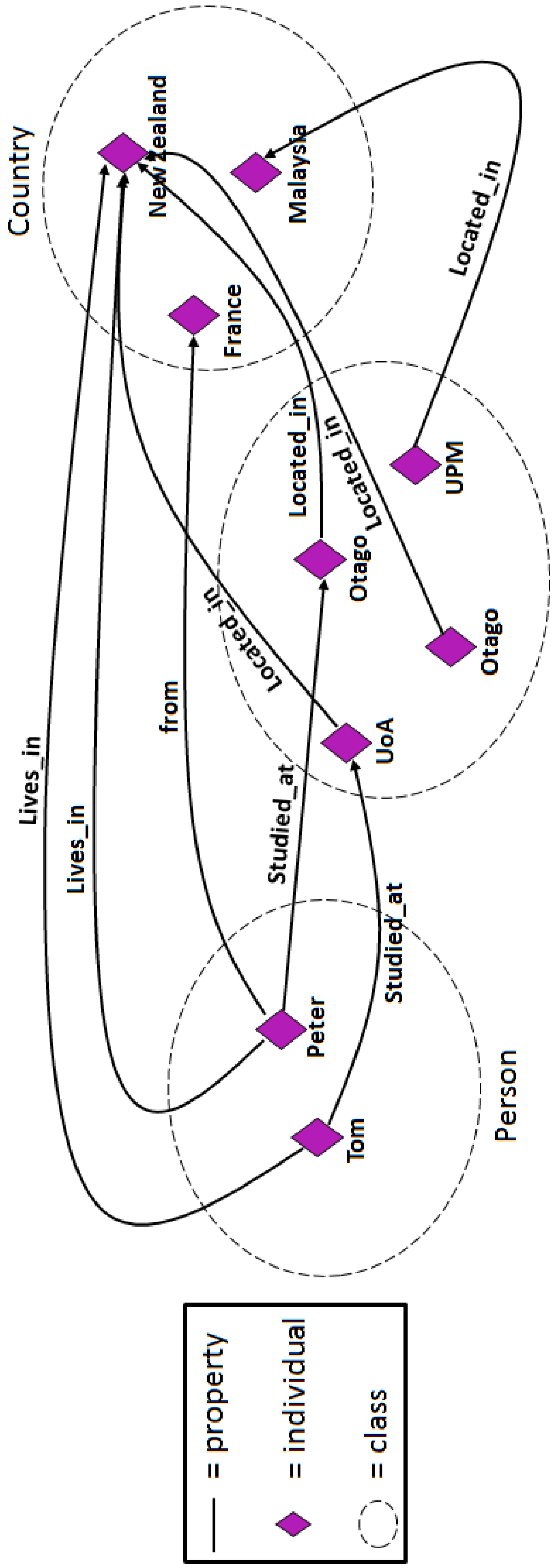

Figure 4.5: Representation of some individuals

Properties

A property is known as a binary relationship between two individuals. For example, the property "Lives_in" might connect an individual "Tom" to the individual "New Zealand". Properties also reflect the inverse concept as well. For example, the inverse of "hasOwner" is "is OwnedBy". Properties can also be limited to have a single value (i.e., Functional properties). They can also represent either transitive or symmetric properties.

OWL properties show relationships. In Protégé, there exist two types of properties: Object Properties and Datatype Properties. Basically, Object Properties indicate a relationship between two individuals. Datatype Properties assign an individual to an XML schema Datatype value or an RDF:literal. Namely, properties illustrate relationships between an individual and data values. OWL also defines another type of property called an Annotation Properties. The annotation properties can be applied to add extra information (i.e., Metadata (data about data)) to the defined classes, individuals, and object/datatype properties. Figure 4.5 depicts an example of each type of property.

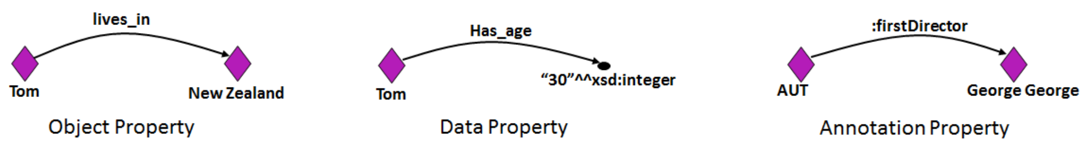

Figure 4.6: Representation of properties

Classes

OWL classes are known as the main concepts, types or universal in an ontology. The classes also contain their own individuals. In fact a class shows a group of different individuals that share common interest. They are expressed using formal descriptions that declare the membership requirements. For example, a "Country" class contains all individuals which are about countries (See Figure 4.5). Classes are also categorised in the hierarchy by superclasses and subclasses of the ontology. One of the main features of OWL is that the superclasses and subclasses can be calculated by an ontology reasoner. Subclasses generally specialise their superclasses. For example, consider the “Country” and “European Country” classes, the “European Country” class can be a subclass of the “Country” class (i.e., The “Country” class is a superclass of “European Country”). This statement can be interpreted in the way that all European countries are as countries; or all members of the of “European Country” class are also members of the “Country” class; or being a European country shows that it is a country.

4.4.2 Ontology Building

In this section, the process of generating an ontology by using the Protégé Ontology Editor has been explained. The process of generating an ontology usually requires 11 steps (Gomez-Perez, Fernández-López & Corcho, 2006):

1. Construct a glossary that shows a set of terms to be used in the ontology along with their natural language definitions, their synonyms and acronyms.
2. Construct a concept taxonomy to categorise concepts.
3. Construct ad hoc binary relation diagrams to recognize ad hoc relationships between concepts.
4. Construct the concept dictionary that contains instances for each concept (i.e., individual, class attributes and ad hoc relations).
5. Explain the details of each ad hoc relation on the ad hoc binary relation diagram.
6. Explain the attribute of each individual that appears in the concept dictionary.
7. Explain the attribute of each class that appears in the concept dictionary.

8. Explain the attribute of each constant. Basically, a constant specifies information relating to the knowledge domain. They always take the same value.

9. Explain formal axioms that have been used for the constant dictionary.

10. Explain rules that are used to infer attribute values.

11. Describe information about each individual.

In the following, the process of generating an ontology has been illustrated. Figures 4.7 and 4.8 show an XML file retrieved through a particular query and different APIs. As mentioned in Section 4.2, an ontology can be developed through different tags available in the XML file. As noted in Section 4.3, abstract and MeshHeading have been used to identify ontology classes and the relationships among them. It is important to consider that key terms used in the abstract not only represent classes at the schema-level but they can also be used as individuals within classes. In fact, these individuals are the children of classes at the instance-level. Figure 4.9 shows that how classes can be extracted via from abstracts and MeshHeading.

```xml
    <PubmedArticle>
    <MedlineCitation Status="MEDLINE" Owner="NLM">
        <PMID Version="1">25328618</PMID>
        <DateCreated>
            <Year>2014</Year>
            <Month>10</Month>
            <Day>20</Day>
        </DateCreated>
        <DateCompleted>
            <Year>2015</Year>
            <Month>08</Month>
            <Day>17</Day>
        </DateCompleted>
        <DateRevised>
            <Year>2016</Year>
            <Month>11</Month>
            <Day>25</Day>
        </DateRevised>
        <Article PubModel="Electronic-eCollection">
            <Journal>
                <ISSN IssnType="Electronic">1937-8688</ISSN>
                <JournalIssue CitedMedium="Internet">
                    <Volume>17</Volume>
                    <PubDate>
                        <Year>2014</Year>
                    </PubDate>
                </JournalIssue>
                <Title>The Pan African medical journal</Title>
                <ISOAbbreviation>Pan Afr Med J</ISOAbbreviation>
            </Journal>
            <ArticleTitle>Tuberculosis arthritis of the metatarsal phalangeal: a rare location.</ArticleTitle>
            <Pagination>
                <MedlinePgn>323</MedlinePgn>
            </Pagination>
            <ELocationID EIdType="doi" ValidYN="Y">10.11604/pamj.2014.17.323.4220</ELocationID>
            <Abstract>
                <AbstractText>Tuberculosis TB is common in countries constituting endemic areas like Morocco, spinal sites represents half of
osteo-articular locations, while peripheral locations in the limbs are rare. The authors relate in this observation the case of a particular
location of tuberculosis arthritis. It is osteoarthritis of the metatarsophalangeal joint of the 2(nd) ray of the foot. Clinical signs were
characterized by a moderately painful swelling of the dorsum of the foot with slow evolution. The definitive diagnosis was histologically
obtained. Clinical cure was achieved after 09 months of medical treatment.</AbstractText>
            </Abstract>
            <AuthorList CompleteYN="Y">
                <Author ValidYN="Y">
                    <LastName>Berrady</LastName>
                    <ForeName>Mohamed Ali</ForeName>
                    <Initials>MA</Initials>
                    <AffiliationInfo>
                        <Affiliation>Department of Orthopaedic Surgery and Traumatology, University Hospital Center Ibn Sina, Rabat,
Morocco.</Affiliation>
                    </AffiliationInfo>
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                <PublicationType UI="D016428">Journal Article</PublicationType>
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                <Year>2014</Year>
                <Month>04</Month>
                <Day>29</Day>
            </ArticleDate>
        </Article>
        <MedlineJournalInfo>
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            <MedlineTA>Pan Afr Med J</MedlineTA>
            <NlmUniqueID>101517926</NlmUniqueID>
        </MedlineJournalInfo>
        <ChemicalList>
            <Chemical>
                <RegistryNumber>0</RegistryNumber>
                <NameOfSubstance UI="D000995">Antitubercular Agents</NameOfSubstance>
            </Chemical>
        </ChemicalList>
        <CitationSubset>IM</CitationSubset>
        <CommentsCorrectionsList>
            …
            …
            …
        </CommentsCorrectionsList>
```


Figure 4.7: A sample xml code for a knowledge item in PubMed

```xml
        <MeshHeadingList>
            <MeshHeading>
                <DescriptorName UI="D000995" MajorTopicYN="N">Antitubercular Agents</DescriptorName>
                <QualifierName UI="Q000627" MajorTopicYN="N">therapeutic use</QualifierName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D006101" MajorTopicYN="N">Granuloma, Giant Cell</DescriptorName>
                <QualifierName UI="Q000000981" MajorTopicYN="N">diagnostic imaging</QualifierName>
                <QualifierName UI="Q000188" MajorTopicYN="N">drug therapy</QualifierName>
                <QualifierName UI="Q000209" MajorTopicYN="N">etiology</QualifierName>
                <QualifierName UI="Q000473" MajorTopicYN="N">pathology</QualifierName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D006801" MajorTopicYN="N">Humans</DescriptorName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D008297" MajorTopicYN="N">Male</DescriptorName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D008682" MajorTopicYN="N">Metatarsal Bones</DescriptorName>
                <QualifierName UI="Q000000981" MajorTopicYN="N">diagnostic imaging</QualifierName>
                <QualifierName UI="Q000473" MajorTopicYN="Y">pathology</QualifierName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D008683" MajorTopicYN="N">Metatarsophalangeal Joint</DescriptorName>
                <QualifierName UI="Q000000981" MajorTopicYN="N">diagnostic imaging</QualifierName>
                <QualifierName UI="Q000473" MajorTopicYN="Y">pathology</QualifierName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D008875" MajorTopicYN="N">Middle Aged</DescriptorName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D011859" MajorTopicYN="N">Radiography</DescriptorName>
            </MeshHeading>
            <MeshHeading>
                <DescriptorName UI="D014394" MajorTopicYN="N">Tuberculosis, Osteoarticular</DescriptorName>
                <QualifierName UI="Q000150" MajorTopicYN="N">complications</QualifierName>
                <QualifierName UI="Q000000981" MajorTopicYN="N">diagnostic imaging</QualifierName>
                <QualifierName UI="Q000188" MajorTopicYN="N">drug therapy</QualifierName>
                <QualifierName UI="Q000473" MajorTopicYN="Y">pathology</QualifierName>
            </MeshHeading>
        </MeshHeadingList>
        <OtherID Source="NLM">PMC4198287</OtherID>
        <KeywordList Owner="NOTNLM">
            <Keyword MajorTopicYN="N">Tuberculosis</Keyword>
            <Keyword MajorTopicYN="N">anti tuberculous chemotherapy</Keyword>
            <Keyword MajorTopicYN="N">metatarsophalangeal joint</Keyword>
            <Keyword MajorTopicYN="N">osteoarthritis</Keyword>
            <Keyword MajorTopicYN="N">sequelae</Keyword>
        </KeywordList>
    </MedlineCitation>
    <PubmedData>
        <History>
            <PubMedPubDate PubStatus="received">
                <Year>2014</Year>
                <Month>03</Month>
                <Day>19</Day>
            </PubMedPubDate>
            <PubMedPubDate PubStatus="accepted">
                <Year>2014</Year>
                <Month>04</Month>
                <Day>06</Day>
            </PubMedPubDate>
            <PubMedPubDate PubStatus="entrez">
                <Year>2014</Year>
                <Month>10</Month>
                <Day>21</Day>
                <Hour>6</Hour>
                <Minute>0</Minute>
            </PubMedPubDate>
            <PubMedPubDate PubStatus="pubmed">
                <Year>2014</Year>
                <Month>10</Month>
                <Day>21</Day>
                <Hour>6</Hour>
                <Minute>0</Minute>
            </PubMedPubDate>
            <PubMedPubDate PubStatus="medline">
                <Year>2015</Year>
                <Month>8</Month>
                <Day>19</Day>
                <Hour>6</Hour>
                <Minute>0</Minute>
            </PubMedPubDate>
        </History>
        <PublicationStatus>epublish</PublicationStatus>
        <ArticleIdList>
            <ArticleId IdType="pubmed">25328618</ArticleId>
            <ArticleId IdType="doi">10.11604/pamj.2014.17.323.4220</ArticleId>
            <ArticleId IdType="pii">PAMJ-17-323</ArticleId>
            <ArticleId IdType="pmc">PMC4198287</ArticleId>
        </ArticleIdList>
    </PubmedData>
</PubmedArticle>
```


Figure 4.8: A sample xml code for a knowledge item in PubMed (continued)

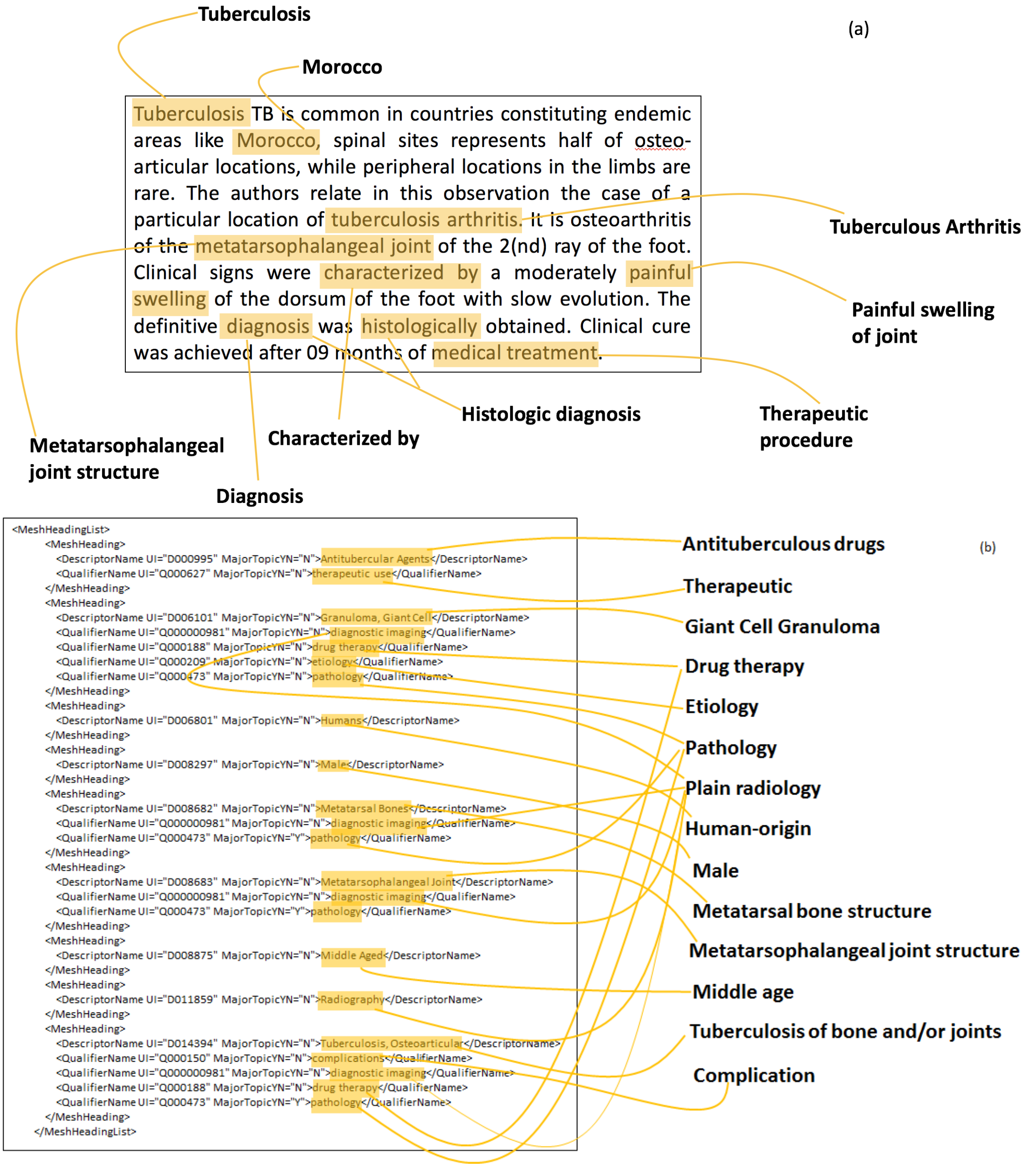


Figure 4.9: (a) extracting concepts from an abstract, (b) extracting concepts from mesh headings

As seen in Figure 4.9 (a), those terms that are matched with the class and concept names used in the UMLS and SNOMED-CT can be extracted through applications mentioned in Section 4.3. These terms can be tuberculosis, Morocco, tuberculosis arthritis, metacarpophalangeal joint, clinical signs, characterized by, painful swelling, diagnosis, histologically, and medical treatment. As mentioned earlier, these classes along with their corresponding subclasses (i.e., the taxonomy) could be extracted using APIs. For example, the "Painful swelling of joint" class is the closet class to "painful swelling" that can be used in the ontology. Figure 4.10 shows the structural information of this class in UMLS and SNOMED-CT. As seen in this Figure, the information "Painful swelling of joint" can be added to the ontology through using relationships and annotations.

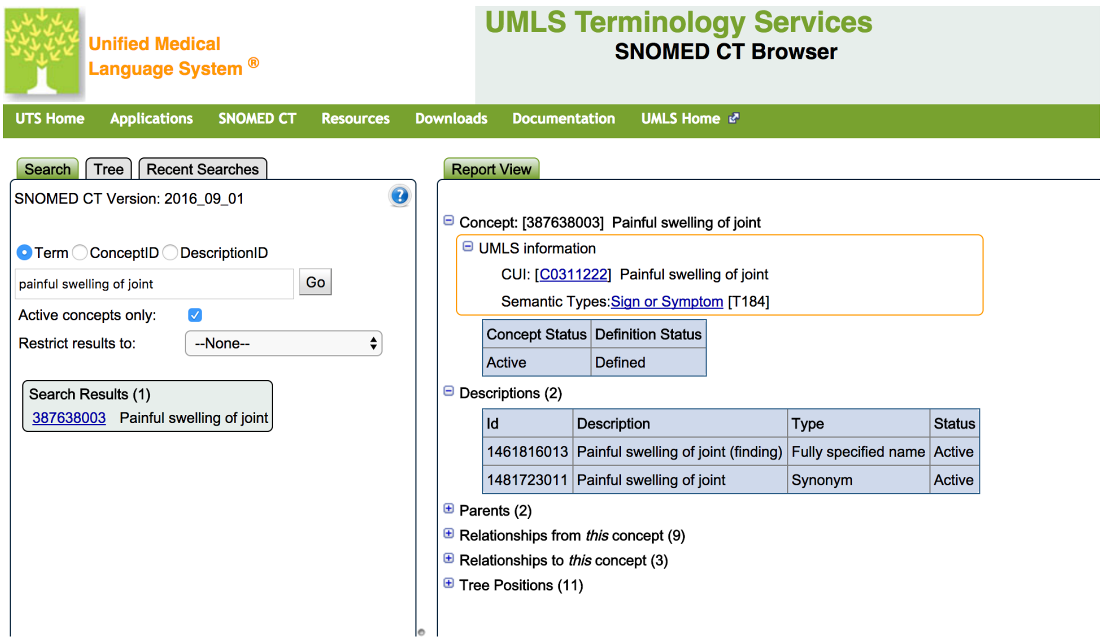


Figure 4.10: Structural information of the "Painful swelling of joint" concept in UMLS

Figure 4.11 shows a defined class in the ontology. As can be seen, some information such as concept ID, CUI, fully specified name, and semantic types can be added to the class as related annotations.

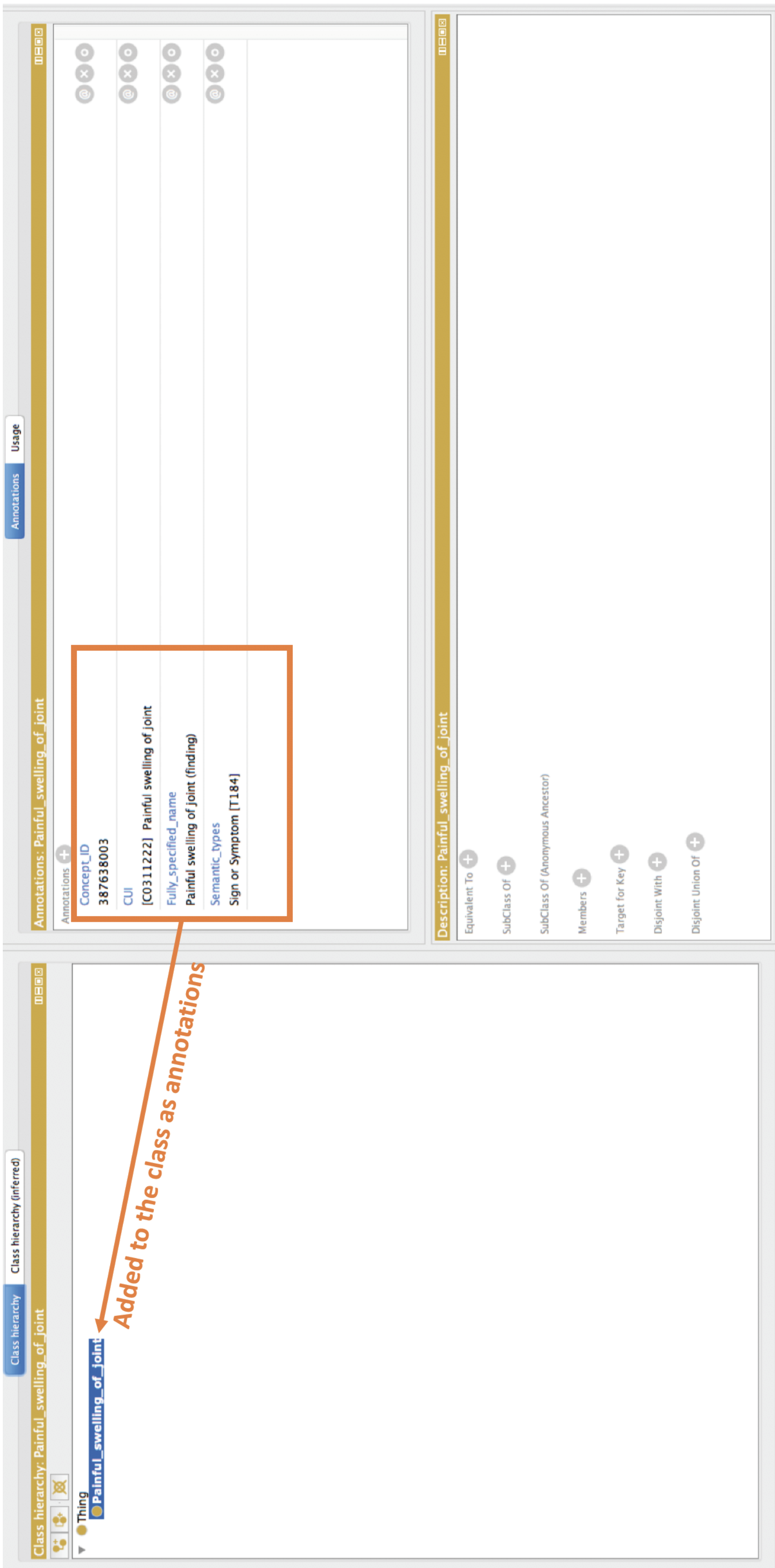


Figure 4.11: Defining the “Painful swelling of joint” class in ontology

In addition, supperclasses were added to the ontology. Superclasses share more general concepts and are usually located at the upper levels of the ontology. In this system, the process of adding a superclass will continue until reaching the highest level (i.e. A particular top concept $THING$) in the SNOMED-CT. Figure 4.12 represents the hierarchical structure of the "Painful swelling of joint" class in the ontology using the OntoGraph tab in Protégé.

As mentioned previously, knowledge will be extracted based on the given query and added to the ontology. In this regard, each extracted knowledge item has a particular ID. Since each query points to a particular disease or condition in the KQA, the related knowledge along with its ID can be added to the related class in the ontology as a new individual. This process helps to store the information related to abstract, date_created, title, PubMed identification (PMID) and publication_type into the ontology. Figure 4.13 shows the selected knowledge (K1) used as an individual in the ontology.

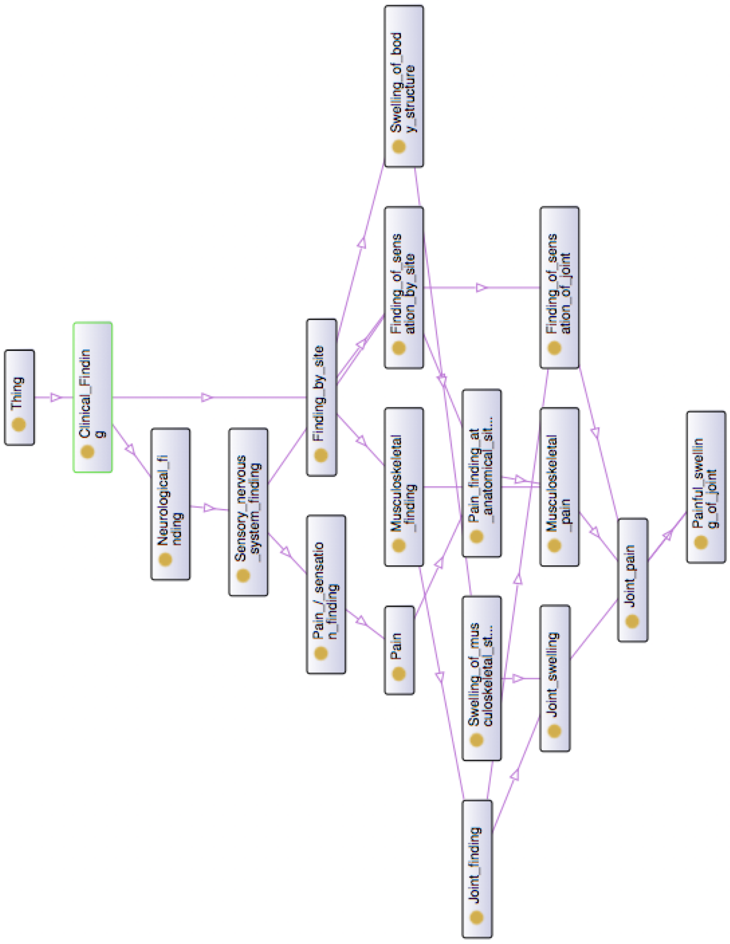


Figure 4.12: The hierarchical structure of the “Painful swelling of joint” class

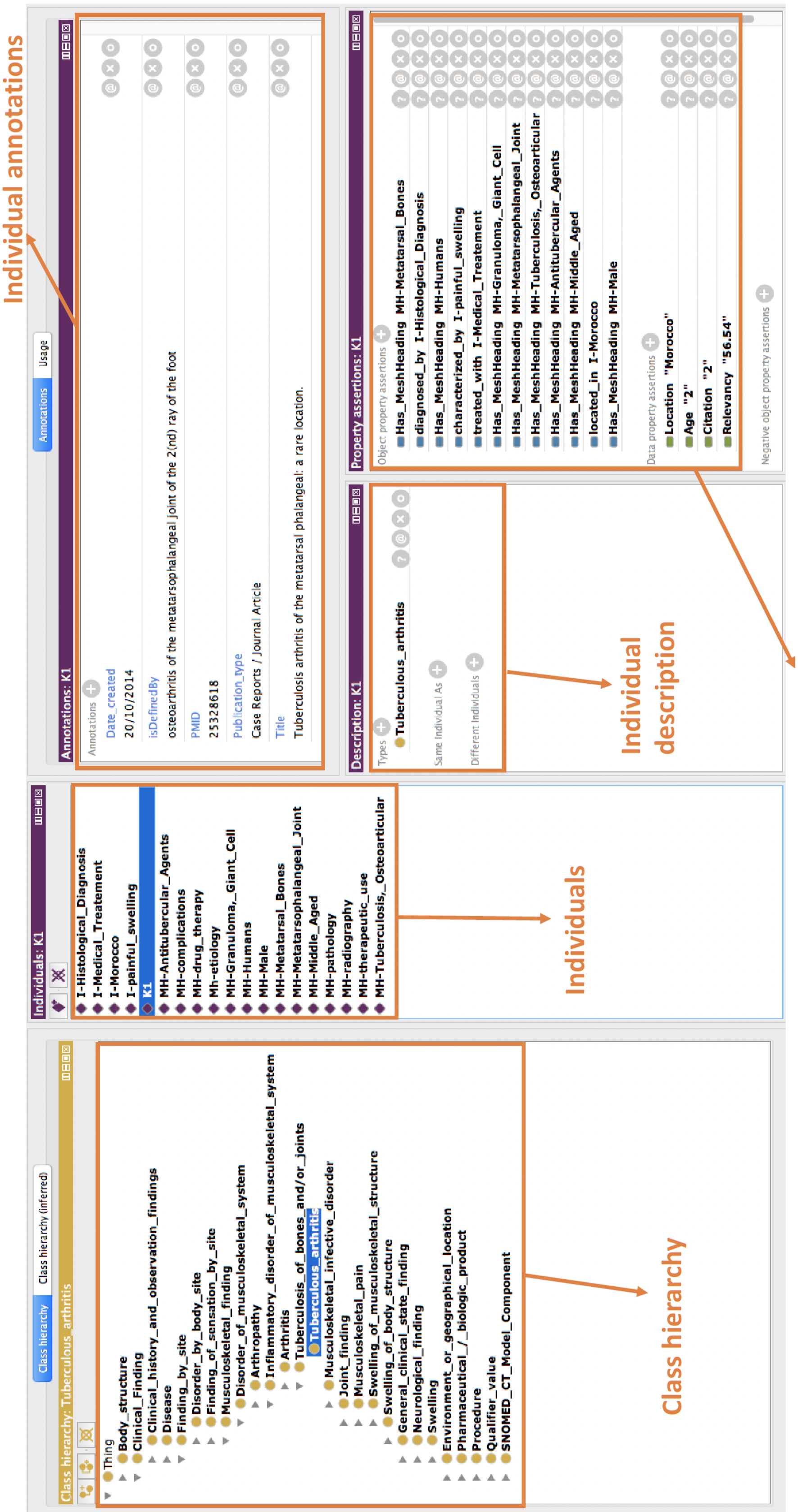


Figure 4.13: Selected knowledge (K1) in instance view

Discovering relationships is the next step in creating an ontology. For example, the relation “Located_in” indicates the location of a particular knowledge item. As shown in Figure 4.14, the location of the “K1” knowledge item is Morocco, which needs to be added to the ontology.

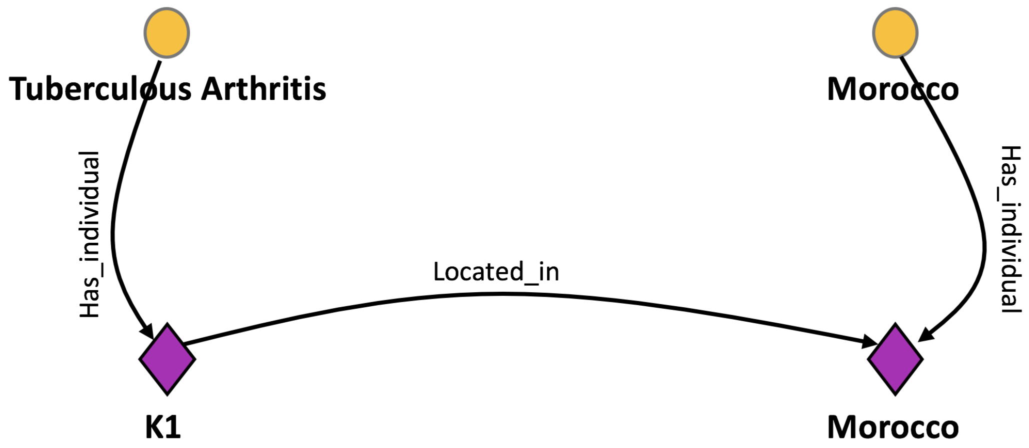


Figure 4.14: A relation between two individuals

In the OWL, the “Has-individual” relationship is a particular relationship between class and individual. In the OWL schema, this relationship has been used for the individuals of a class in the lowest level of the ontology. However, based on the hierarchy theory, if a subclass of a superclass has some particular individuals, then the superclass has those individuals as well. The “characterized_by” relationship defined in the OWL also can be used to show some specific features of “Tuberculosis Arthritis”. This relationship adds a particular link between “K1” and “painful swelling”. This task can be completed using object property assertion provided in Protégé. Figure 4.15 shows how to use this relationship.

There are some specific tags used in MeshHeadings such as “Qualifier Name”. The information related to this tag can be added to an instance and MeshHeading through the “QualifierName” relationship. Figure 4.16 represents how this relationship can be added using object property assertion provided in Protégé.

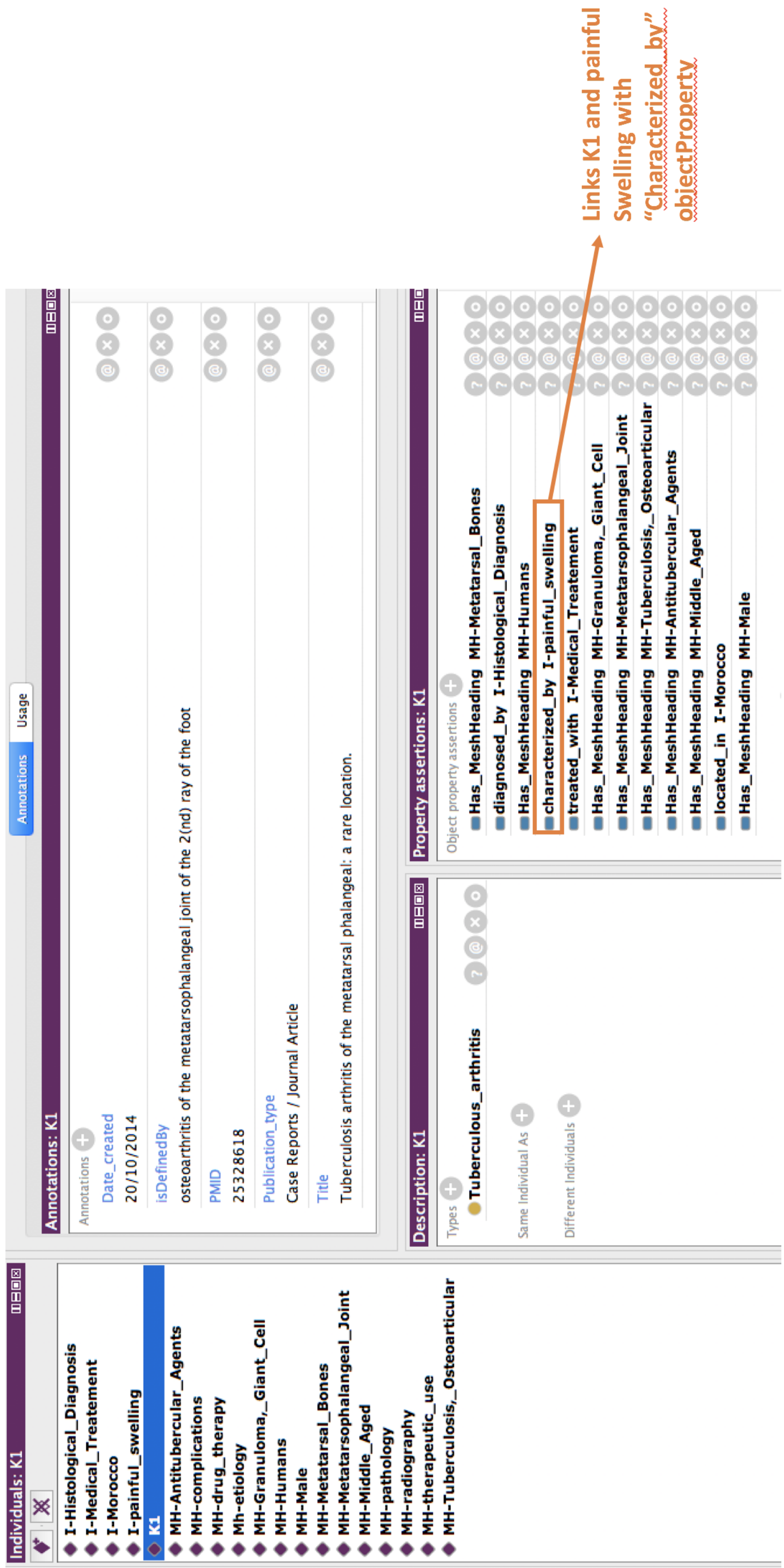


Figure 4.15: An example of object property assertion

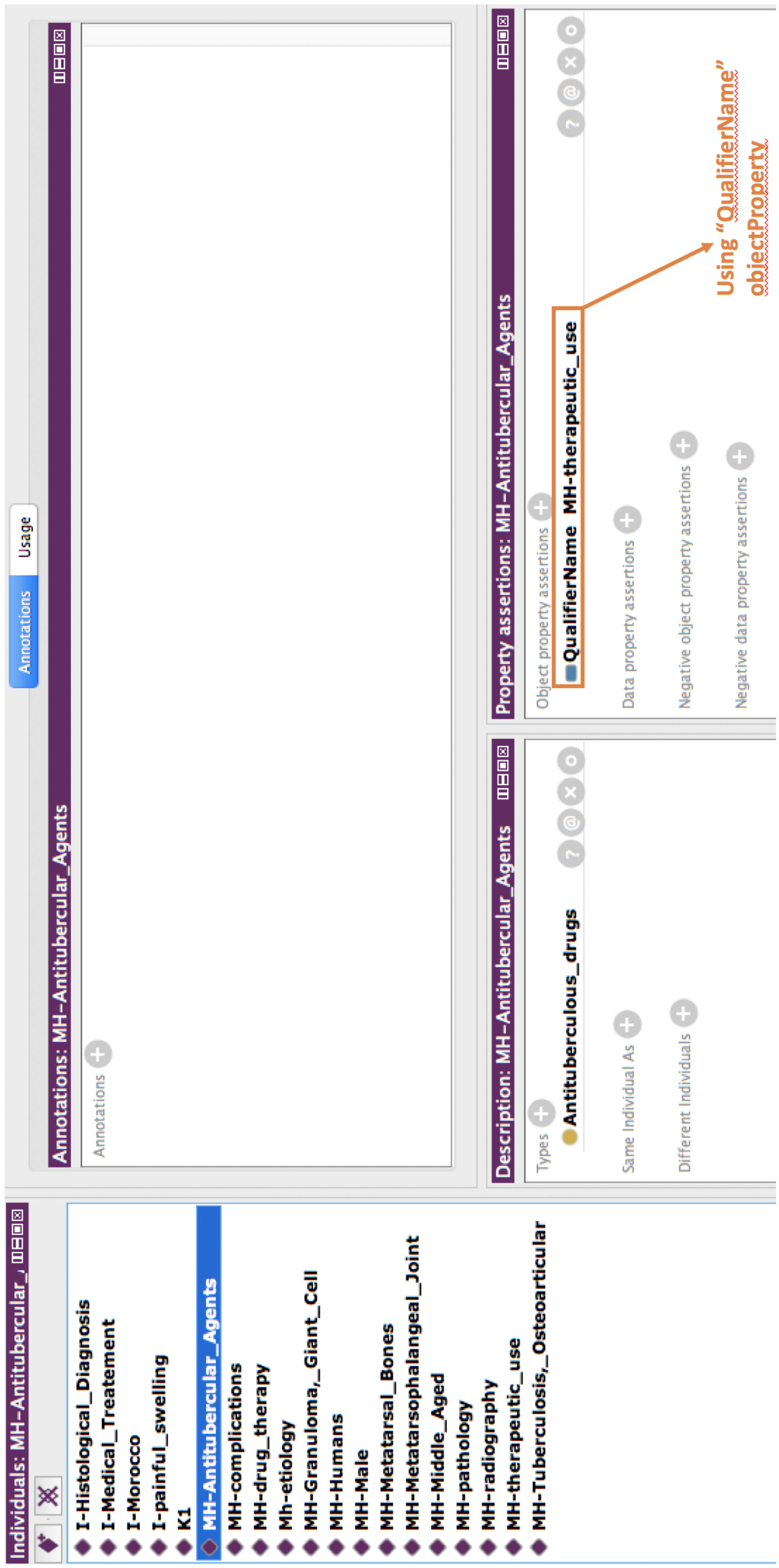


Figure 4.16: Assigning information to a MeshHeading using the “QualifierName” ObjectProperty

Figure 4.17 shows the ontology generated using OntoGraph tab in Protégé. The related OWL code has been included on the digital Appendix of the thesis. The quality of the extracted knowledge can be calculated by reading the ontological structure of the knowledge. This scenario will be applied to construct an ontology for each extracted knowledge item. The next chapter explains the process of evaluating the quality of an ontological knowledge item in detail, forming the main part of this thesis.

4.5 Chapter Summary

This chapter explains the process of extracting and generating knowledge in an ontological structure using SW technologies. This chapter discusses how the textual knowledge extracted from KSs can be transformed into the ontological structure to facilitate the process of knowledge evaluation. This chapter also illustrates different processes for extracting and discovering concepts from knowledge. It then discusses different concepts used in an ontological structure. Finally, the process of constructing an ontological knowledge has been explained in detail.

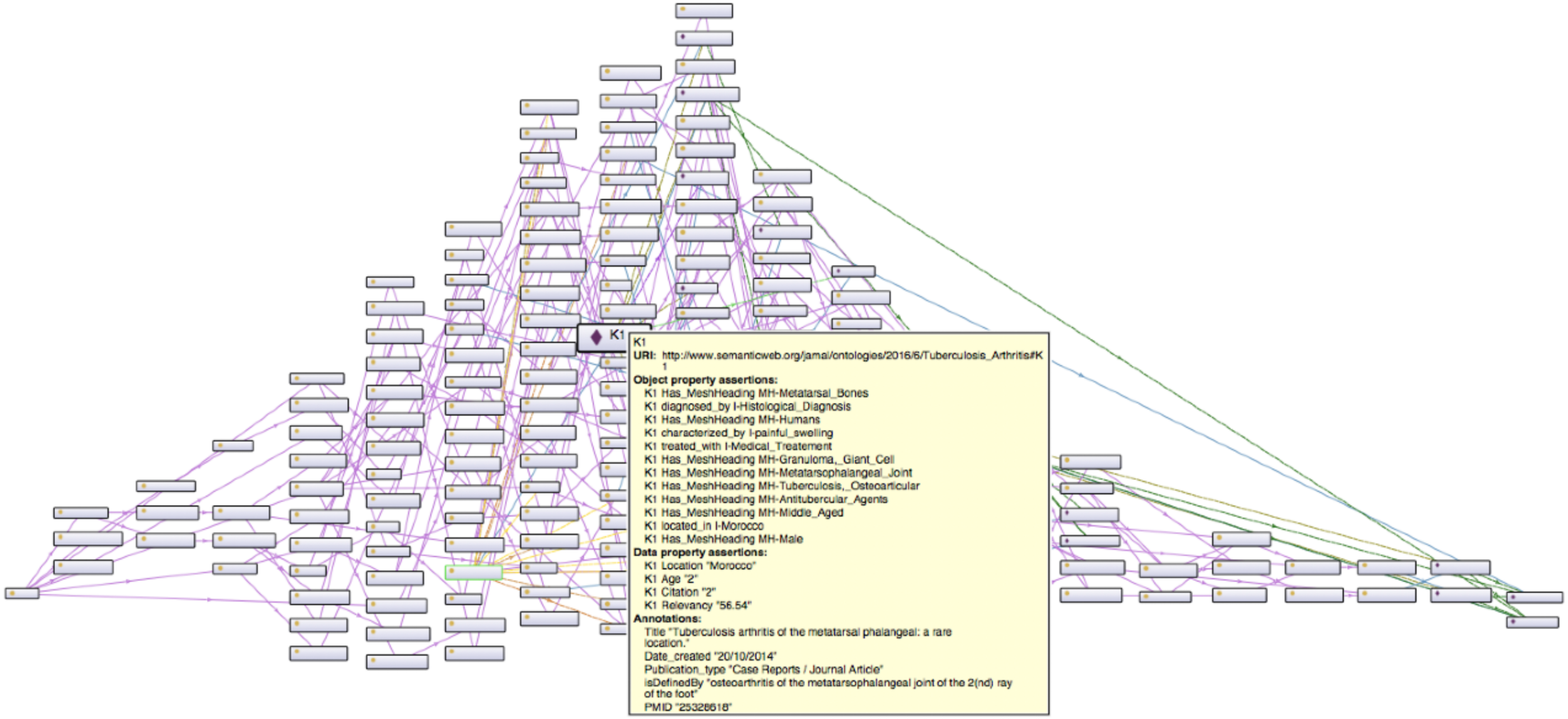


Figure 4.17: Completed ontology for the selected knowledge item (i.e. K1)

Chapter 5

Knowledge Quality Assessment

5.1 Introduction

Within CDSSs, assessing the quality of knowledge should be an initial activity to help practitioners to make sound decisions. Access to the highest quality knowledge by health practitioners has been a goal of health providers around the world, including New Zealand, to supply high quality of care. Assessing the quality of knowledge should be a feature of KA in the CDSS. Up to now it appears that, the quality of knowledge used in the CDSSs has only been considered to a minor extent. This chapter explains how to assess the quality of knowledge using knowledge QMs. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

5.2 Knowledge QMs

The primary motivation for this research is to propose knowledge QMs for the KQA to facilitate KA for the CDSSs. In order to make a correct decision, knowledge must be accurate, relevant and up-to-date. Existing methods do not provide a clear vision for assessing the quality of clinical knowledge used in the CDSSs. Thereby, there is an essential need to develop an approach for KA in the CDSSs to check the quality of extracted knowledge from KSs. The KQA aims to cover this gap.

Yoo et al. noted that knowledge quality should be intrinsically right, contextually relevant, and practically actionable (Yoo et al., 2011). Based on the Kyoon Yoo knowledge quality model, knowledge QMs can be classified into three general categories; intrinsic, contextual, and actionable. In this research, we have adapted and modified the Kyoon Yoo model for categorizing knowledge QMs. The knowledge QMs were identified by reviewing articles on knowledge quality in the context of healthcare (Refer to Section 2.6).

Based on our categorization, intrinsic knowledge QMs are knowledge QMs used to assess the backbone of knowledge. Contextual knowledge QMs show how much the extracted knowledge is relevant, reliable, and accurate to a given user query. Actionable knowledge QM indicates that the knowledge is provided in a timely manner for further use. Figure 5.1 shows the three knowledge QMs categories that have been proposed for this research. The summary of categorized knowledge QMs is shown in Table 5.1. This table shows the description of candidate knowledge QMs to be used in the knowledge assessment of the KQA.

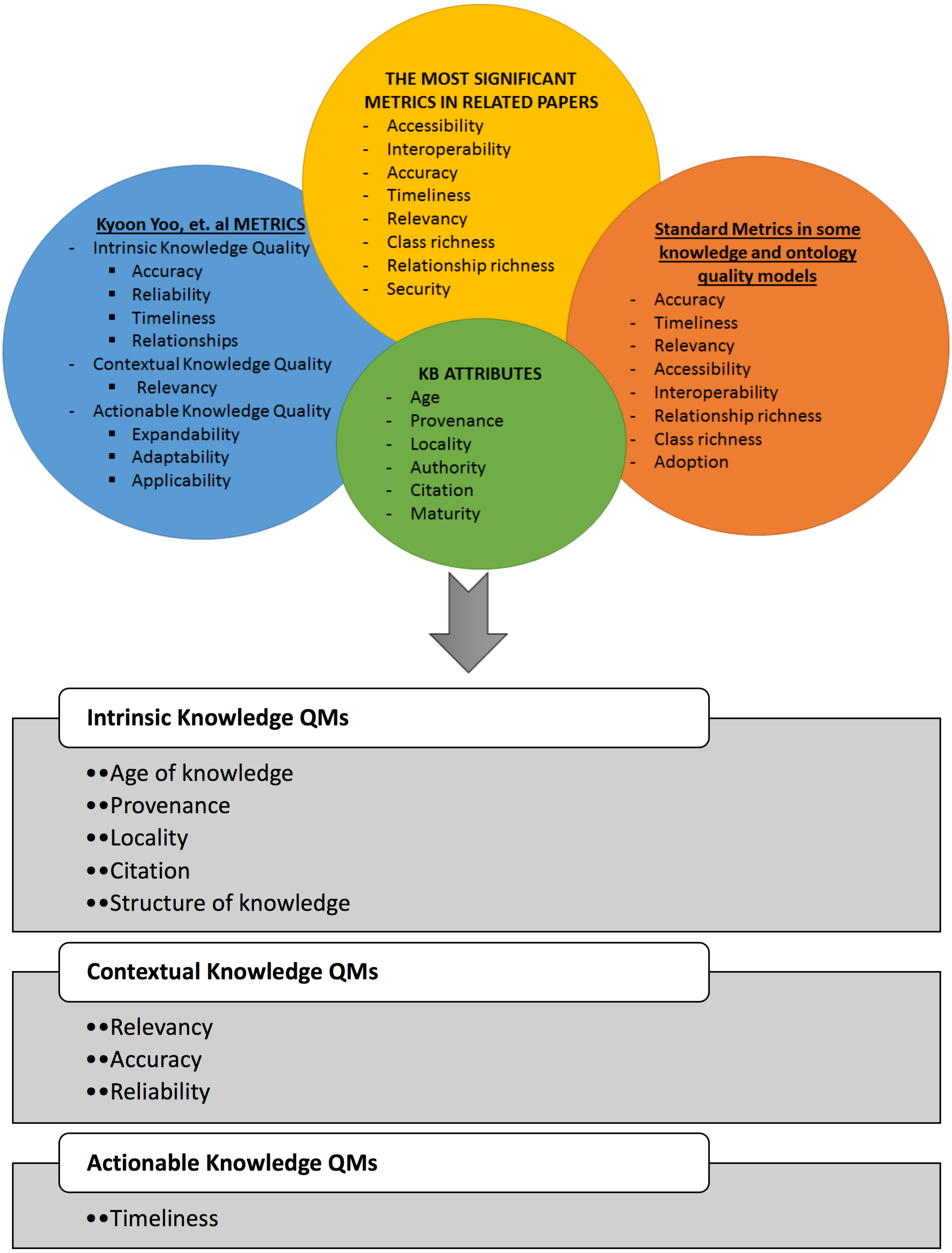


Figure 5.1: Candidate knowledge QMs for assessing quality of knowledge

Table 5.1: Candidate knowledge QMs for the KQA

Knowledge QM		Description
Intrinsic	Age of knowledge	It indicates how old the knowledge is.
	Provenance	The knowledge should be based on valid authority.
	Locality	It is located in the location that the knowledge was created.
	Structure	In order to analyse the quality of knowledge, it is better to represent its structure in the machine understandable format(E.g. XML and OWL). An existing method is to represent knowledge in the ontological structure to facilitate the process of knowledge assessment.
	Citation	It illustrates the number of citations, references, and quotes the knowledge item has had for different purposes.
Contextual	Accuracy	How accurate the knowledge is.
	Reliability	The KA will produce the same answer for the same question in different KSs.
	Relevancy	The knowledge contains relevant information to support the user query.
Actionable	Timeliness	The KS produces an answer in an appropriate time.

5.3 Rating and validating knowledge QMs

To rate and validate the candidate knowledge QMs, a questionnaire was conducted among health experts (i.e. health informatics scholars and practitioners) in HiNZ and ACHI. The questionnaire is attached in Appendix B. In this questionnaire, the experts were able to provide their comments about knowledge QMs. The questionnaire collected results from 10 health experts. Table 5.2 shows the questionnaire results for the candidate knowledge QMs rated for use in the KQA. In this table, the rating is on a scale between 1-5 (1: Not at all Important, 2: Slightly Important, 3: Moderately Important, 4: Quite Important, 5: Extremely Important).

The questionnaire results show that CDSSs require intelligent procedures to check the quality of the extracted knowledge using knowledge QMs. In order to measure the quality of retrieved knowledge, in this research a combination of intrinsic and contextual knowledge QMs have been used. The actionable knowledge QM (i.e. Timeliness) is out of the scope of this research. As the actionable knowledge QM is related to the quality of knowledge after being incorporated into the decision making process, the main goal of KQA is to check the quality of knowledge before use in the decision making process. In this research, the KQA is developed by assessing accuracy and relevancy as mentioned in the contextual knowledge QMs, as these are the most highly rated knowledge QMs. Additionally, some intrinsic knowledge QMs are used in the process of assessing the quality of knowledge. From the intrinsic knowledge QMs category, age of knowledge, structure, and citation are also considered. As seen in Table 5.2, although the reliability knowledge QM was placed a second among the knowledge QMs, applying this knowledge QM has been postponed for the time being the future. The accuracy and relevancy knowledge QMs from the contextual category are those to be considered. The decision not to include provenance, was taken because it is related to the reputation of a KS. For the purpose of this thesis, we assume that the reputations of the KSs are the same and valid. Moreover, we assume that the knowledge extracted for a clinical concept does not belong to a specific region, so, locality will not be considered in the knowledge assessment at this time.

Apart from the above results achieved by the questionnaire, the following are some comments collected from participants that identify some knowledge QMs that could be useful for future development of the KQA:

Person A: Level of evidence and level of recommendation. This gives flexibility to the CDSS so that it gives more freedom to the clinicians. These metrics are found in practice guidelines.

Person B: The knowledge is in a form that computerized decision support system can use. It is equally important that the knowledge is in a form that the user can use - presentation of information to the user within a CDSS is vital for its safe and effective use.

Person C: Validity (the knowledge can be confirmed by using different sources)

Person D: Normalization (in the database sense: 3NF). All the ills of denormalized databases are being presented to us as clinicians because database professionals have ignored the importance of normalization.

Person E: Weighting. No diagnosis is cast in stone; no observation is 100% "right." At autopsy, 8–30% of diagnoses are incorrect. Diagnoses should always be considered to be reputable diagnostic hypotheses. It is important to know how sure a clinician is about an assertion, an affordance not provided by most current EHRs and the like.

Person F: Ability to give feedback (to point out possible error or exception)

Person G: To me, the structure is NOT just plonking things in XML. It is about the optimal presentation of the minimum of necessary data required for the clinician to do their job. It is difficult, and not well done (as shown in the Epic co-trimoxazole incident, and many others besides. Epic may well be better than most).

Person H: Citations are tricky. It is important that evidence can be traced to its source but not always practicable to include citations in rapid easy to read guidelines.

Table 5.2: Survey results rating and validating candidate knowledge QMs

Quality Metric	Participants (Rating 1-5)										Average Rating	Total	Count					
	A	B	C	D	E	F	G	H	I	J			1	2	3	4	5	N/A
Accuracy	5	4	5	5	5	4	5	5	5	4	**4.7**	47				3	7	
Reliability	5	4	5	5	5	4	5	5	5	4	**4.7**	47				3	7	
Provenance	4	4	4	5	5	4	4	2	5	4	**4.1**	41		1		6	3	
Relevancy	4	3	5	4	5	3	3	3	5	4	**3.9**	39			4	3	3	
Timeliness	5	3	4	4	3	3	4	3	5	4	**3.8**	38			4	4	2	
Age of knowledge	4	2	4	4	5	3	5	3	5	3	**3.8**	38		1	3	3	3	
Citation	4	3	4	5	4	2	3	3	4	4	**3.6**	36		1	3	5	1	
Structure	N/A	3	4	4	5	3	3	4	4	4	**3.4**	34			3	5	1	1
Locality	5	2	2	3	3	2	3	3	4	4	**3.1**	31		3	4	2	1	

5.4 Evaluating knowledge quality using knowledge QMs

This section explains how knowledge QMs can be used to assess the quality of knowledge. As previously mentioned, the actionable knowledge QM is not going to be assessed in this research as it is related to post-evaluation of knowledge (i.e., the actionable knowledge QM will be assessed when the knowledge has been delivered.). The main purpose of this research is to check the quality of knowledge before its delivery for decision making. In this research, some intrinsic knowledge QMs (Age of knowledge, Structure, and Citation) which are used for assessing the backbone of knowledge along with some contextual knowledge QMs (Relevancy and Accuracy) are considered. Before going into detail about intrinsic and contextual knowledge QMs used in the KQA, the main mechanism for checking and ranking the extracted knowledge is explained.

5.4.1 Main mechanism for checking and ranking knowledge in the KQA

In this section, the KQA mechanism for checking and ranking the extracted knowledge from a KS such as PubMed is illustrated. As seen in Figure 5.2, the KQA mechanism will be applied to the results obtained by the KS. Based on the motivation of this research, which has been explained in Chapter 1, results achieved from the current KS (i.e. PubMed) suffer from a lack of knowledge quality assessment. As previously explained in Chapter 4, in this research, the knowledge items (i.e., articles) used for quality assessment have been transformed into ontological structures. If there is no appropriate knowledge for the query in the central knowledge repository of the KQA (explained in Section 3.4.3), the KQA considers the first knowledge item obtained from a KS as the main knowledge item. It then checks the quality of any other knowledge item by comparing it to the main knowledge item. After evaluating knowledge quality and assigning a KQI to any knowledge item, the knowledge will be ranked from the highest KQI score to the lowest. The ranked knowledge will then be delivered to the CDSS and recorded in the central knowledge repository for use in decision making.

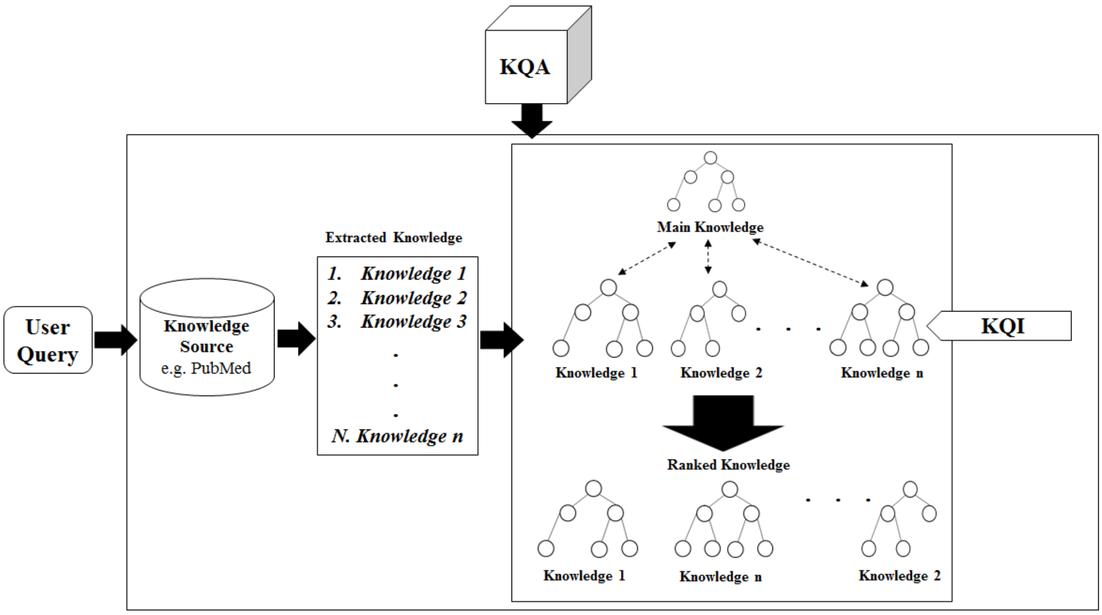


Figure 5.2: The framework of the main mechanism for checking and ranking knowledge in the KQA

5.4.2 The principles of ontological structure in the KQA

As discussed in Chapter 4, the knowledge retrieved from KSs is transformed to an ontological structure to be used in the CDSSs. The reason behind this assumption is that ontological-based knowledge is more suitable for machines as they provide a machine understandable structure. In this thesis, an ontology contains classes, properties, and relationships of individuals that exist for a specific domain of interest. The definition of ontology that has applied in this thesis is as follow.

Definition (Ontology): An Ontology is a description O := (*T*, *C*, *THING*, *CH*, *R*, *I*), which consists of

- A set of **Terms** T: Each term can be represented as a set of lexical items for naming classes or concepts in the ontology, i.e., T^C . Each term can also be used as a set of lexical items for naming relationships, i.e., T^R. T is a set of terms which has been built from the union of T^C and T^R, i.e., $T := T^C \cup T^R$.

- A set of **Classes** C: represents a set of concepts in the ontology.

- A particular top concept $THING$: is above every other class in the ontology. Namely, it can be considered as the root of the ontology.

- A set of **Individuals** I: represents a set of instances or objects within classes in the ontology.

- A **Class Hierarchy** CH: is a taxonomy of concepts. In this taxonomy, concepts are related by transitive relations.

- A set of **Relationships** R refers to links between concepts or individuals in the ontology, i.g., $r(i_1, i_2)$ specifies a 2-tuple (D_r, R_r). The domain (D_r) and range (R_r) of a property links individual i_1 to individual i_2 . In the case of property, if a property links individual i_1 to individual i_2, then the i_1 qualifies as a type of thing specified in the D_r. The R_r can be defined exactly as the D_r. The R_r should be applied to the i_2.

5.4.3 Intrinsic knowledge QM evaluation

This section shows the evaluation of intrinsic knowledge QMs for assessing the quality of knowledge. In this section, all of the intrinsic knowledge QMs are defined, however, only age of knowledge, citation, and structure QMs are considered for the KQA. Any of the following knowledge QMs will be applied to the ontological structures of knowledge as annotations and attributes.

Age of knowledge

This knowledge QM represents how old a knowledge item is. Formally, the age of knowledge (Age) is defined as the subtraction of knowledge date creation ($Date_C$; subtracted) from the current date ($Date$; minuend). The result will be a number of days, months and years since that knowledge item was created.

$$Age = |Date - Date_C| \tag{5.1}$$

Example 1. Imagine that the date of creation for a knowledge item (K_i) is 01.10.2010. If the current date is 01.03.2017 then the age of knowledge is:

$$Age_{K_i} = |01.03.2017 - 01.10.2010| = 6^{Years}/5^{Months}$$

Provenance

This knowledge QM shows where the knowledge item was extracted from a valid KS.

$$P = \begin{cases} 1, & \text{if KS } is\ valid, \\ 0, & \text{otherwise.} \end{cases} \tag{5.2}$$

As an example, if the knowledge extracted from PubMed, P for that knowledge is 1.

Locality

This knowledge QM shows where the knowledge is located.

$$K_{Location} = \{Location | K\, is\, generated\} \tag{5.3}$$

For instance, if the knowledge published in a New Zealand company, the locality will be New Zealand.

Citation

This knowledge QM shows how many times the knowledge item is cited in other KSs.

$$Cite = |K_{Citation}| \tag{5.4}$$

Structure

The extracted knowledge is transformed into an ontological structure (using OWL language). The structure of an ontological knowledge item contains four main factors; Class Maturity (CM), Relationship Maturity (RM), Attribute Maturity (AM), and Inheritance Maturity (IM). In the LR, some quality models used the terms relationship richness, class richness, attribute richness, and inheritance richness in their definitions. In this thesis, we used maturity rather than richness as it conveys a better meaning. The structure of knowledge (S_K) can be calculated by Equation (5.5):

$$S_K = \frac{RM + CM + AM + IM}{4} \tag{5.5}$$

The reason behind using average as a calculation for S_K rather than sum or product of factors is that the average can give a balanced score for S_K. In the following, all of these factors used to compute the structure knowledge QM are defined.

a) Relationship Maturity (RM)

An (RM) is a factor that can be measured at two different levels of the ontology: relationship at the schema level (RM_S) and relationship at the instance level (RM_I). An ontology does not only contain superclass-subclass relationships, there may also be some relationships among classes which are not in the same hierarchy. The RM_S can be calculated by dividing the number of relationships (R) on the sum of the total number of subclasses (Sub) along with the R.

$$RM_S = \frac{|R|}{|Sub| + |R|} \tag{5.6}$$

In this case, those relationships will be considered which have been defined based on the object property relation. More precisely, those relationships with labels of "Has_subclass" and "Has_individual" will not be considered for $|R|$. Therefore, the total number of relationships is the total number of individual relationships as well as class relationships. To compute the total number of subclasses, we first need to calculate the total number of subclasses of each particular class, and then calculate the summations of the total number of subclasses. It is important to mention that we did not consider those classes that are placed at the highest level of an ontology. More precisely, those classes which are subclasses of the $THING$ class, as $THING$ is the superclass of all classes in ontology.

The result of RM_S shows how rich the relationships between classes are. RM_S close to zero indicates that the majority of the relationships in the ontology are superclass-subclass relationships. RM_S close to one also indicates that aside from superclass-subclass relationships, there exist other relationships among different classes of ontology which might not be in the same hierarchy.

The RM_I indicates to what degree the relationships among classes at the schema-level are used by individuals at instance level.The RM_I score of a class c_n can be calculated by Equation (5.7).

$$RM_I = \frac{|R(i_n, i_m)) \mid i_n \in I(c_n) \wedge i_m \in I(c_m)|}{|R(c_n, c_m)|} \tag{5.7}$$

where the nominator of the fraction shows the total number of relationships among individuals of particular classes c_n and c_m at instance level . The denominator of the fraction shows the total number of relationships among classes c_n and c_m at schema level.

Low RM_I score indicates that individuals at the instance level utilize few class relationships at the schema level, while a high RM_I score shows that individuals utilize more relationships defined at schema level.

Example 2. To get a better understanding of the RM_S and RM_I definitions, consider Figure 5.3 which shows the calculation of RM for two ontologies. In this Figure, c_n (e.g. c_1) represents a class of an ontology, and i_n (e.g. i_1) shows an individual of a class in the ontology. The total number of relationship in the ontology (a) is 6. The relationships consist of $R(c_2, c_4)$, $R(c_4, c_5)$, $R(c_1, c_5)$, $R(i_1, i_2)$, $R(i_1, i_3)$, and $R(i_2, i_3)$. Based on this scenario, the total number of relationships in the ontology (b) is 12. The number of subclasses for each particular class has been calculated in the ontology (a) as follows.

$$|Sub_{c_1}| = 2, |Sub_{c_2}| = 0,\ |Sub_{c_3}| = 2,\ |Sub_{c_4}| = 0,\ |Sub_{c_5}| = 0$$

$$|Sub| = \sum_{n=1}^{5} |Sub_{c_n}| = 4$$

Additionally, the total number of subclasses in the ontology (b) is $|Sub| = 7$. Based on the explanation in the definitions of RM_S, RM_I, the RM can be computed as follows.

(a)

$$RM_S = \frac{6}{6+4} = 0.6$$

$$RM_I = \frac{3}{3} = 1$$

$$RM = \frac{1+0.6}{2} = 0.8$$

(b)

$$RM_S = \frac{12}{7+12} = 0.63$$

$$RM_I = \frac{7}{5} = 1.4$$

$$RM = \frac{1.4+0.63}{2} = 1.015$$

By comparing the value of RM obtained from these two ontologies, we can conclude that ontology (b) contains more relationships when compared with ontology (a). It is important to note that individuals of ontology (b) have a majority of their relationships in the classes at schema level. Therefore, ontology (b) has higher priority than ontology (a) in terms of RM.

b) Class Maturity (CM)

This factor is based on sharing instances among concepts of knowledge (i.e. classes in the ontology). It shows how individuals are used among the classes. The Equation (5.8) shows how to measure this factor.

$$CM = \frac{|C^I|}{|C|} \tag{5.8}$$

where C^I is the number of classes that have individuals within them, and C is the total number of classes defined in the ontology.

A low CM score indicates that the knowledge item does not have enough information to exemplify concepts of the ontology, while a high CM score shows how the knowledge item is rich in its use of classes.

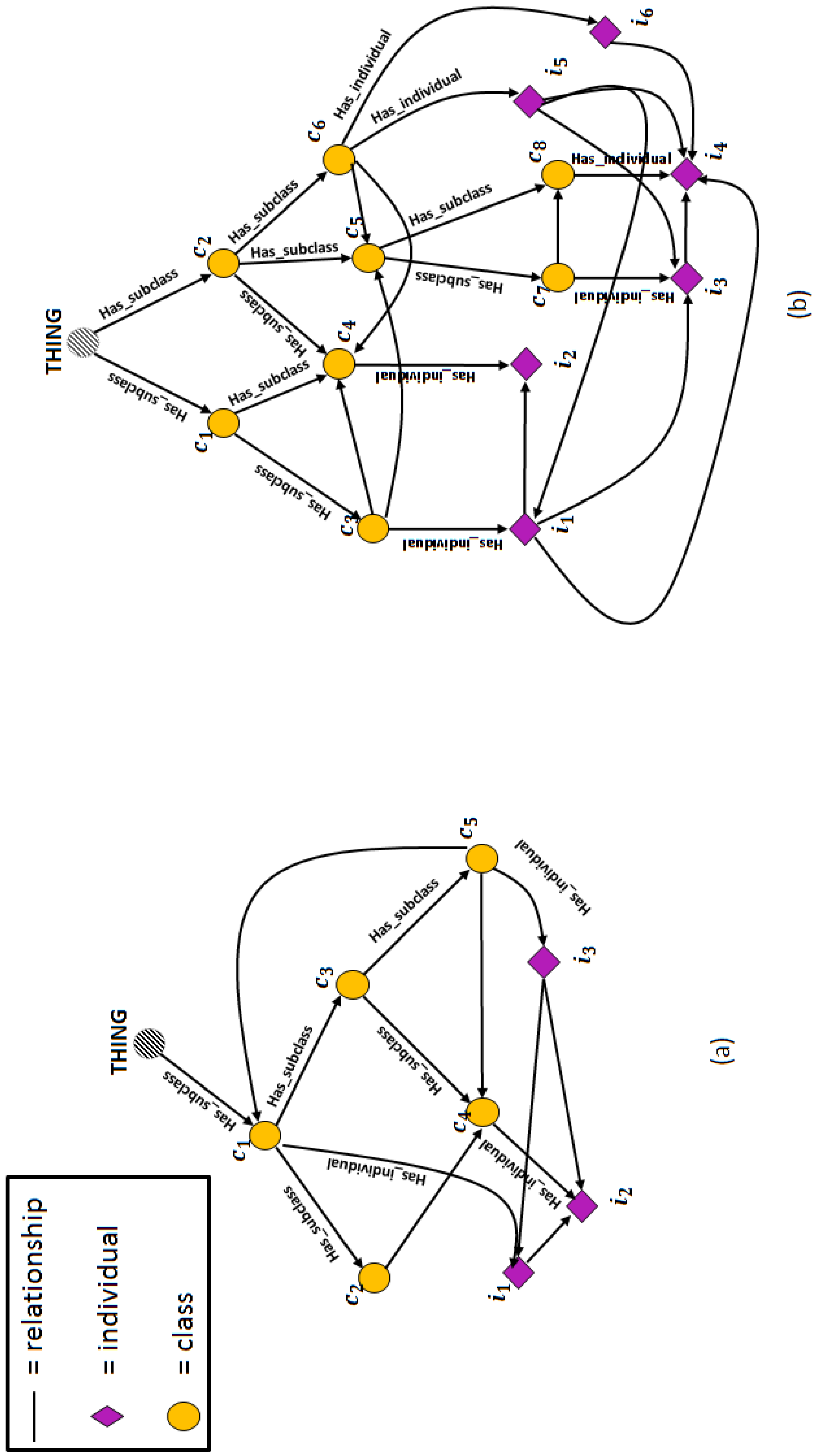


Figure 5.3: Two sample ontologies

Example 3. the CM values for the ontologies shown in Figure 5.3 have been described as follows. The total number of classes in the lowest levels of ontologies (a) and (b) (those classes that contain individuals) are 3 and 5, correspondingly. The total number of classes in these two ontologies are 5 and 8, respectively. Therefore, the value of CM for each ontology is:

a) $CM = \frac{3}{5} = 0.6$ b) $CM = \frac{5}{8} = 0.625$

The obtained results show that ontology (b) contains more data and information than ontology (a).

c) Attribute Maturity (AM)

The AM factor indicates how much information is available for classes of the ontology. A low AM score shows that the ontology provides less information about each class, while a high AM score indicates that there are lots of attributes for each class of the ontology. Equation (5.9) shows how this factor is measured.

$$AM = \frac{|annotation|}{|C|} \tag{5.9}$$

where $|annotation|$ means the number of meta-data (e.g. attributes, and information) for classes and individuals.

d) Inheritance Maturity (IM)

The IM shows how the information in the knowledge item is organized in the ontology structure. If the information is organized in multiple levels of CH in the ontology (Vertical ontology), the ontology might contain more detail. On the other hand, if the ontology has few levels of class hierarchy to represent information (Horizontal ontology), the ontology might be about general concepts. Usually, classes in a vertical ontology have fewer subclasses when compared with classes in a horizontal ontology. To measure this factor, Equation (5.10) has been applied to the KQA.

$$IM = \frac{\sum_{c_n \in C} |Sub(c_n, CH)|}{|C|} \tag{5.10}$$

where $|Sub(c_i, CH)|$ is the number of subclasses of class c_n.

Low IM score shows a detailed ontology with a vertical structure, while a high score represents a horizontal structure ontology with general concepts.

Example 4. Consider the ontologies shown in Figure 5.4. To calculate the IM score, we first need to calculate the total number of subclasses for each class of the ontology. The total number of subclasses divided by the total number of classes in ontology shows the IM score for a particular ontology. The IM scores for the ontologies (a) and (b) as illustrated in Figure 5.4 is 0.92 and 0.9, respectively. The results show that ontology (a) might contain more general concepts compared with ontology (b) that may provide more detailed knowledge.

a) $IM = \frac{12}{13} \cong 0.92$ b) $IM = \frac{9}{10} = 0.9$

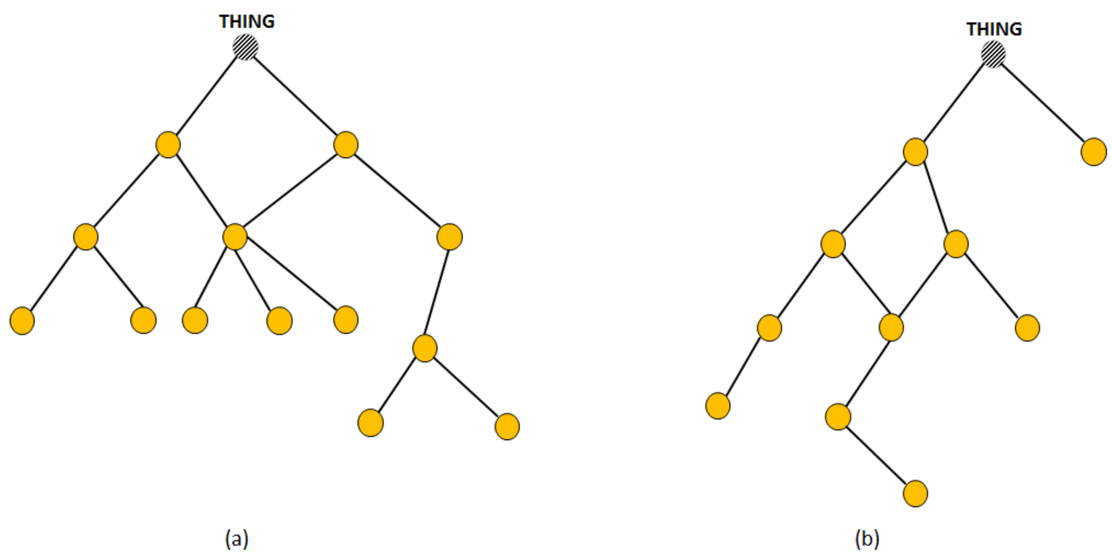


Figure 5.4: Sample ontologies for calculating IM

5.4.4 Contextual knowledge QM evaluation

In this section, the contextual knowledge QMs including relevancy and accuracy will be defined. To assess relevancy for each knowledge item, one of the most popular techniques in information retrieval called Term Frequency-Inverse Document Frequency (TF-IDF) (Ramos et al., 2003) is applied. We also use an ontology comparison mechanism (ontology matching and ontology similarity) to check how accurate the knowledge item is compared to others.

Relevancy

In this part, we focused on identifying a relevancy knowledge QM that can be used for assessing the quality of knowledge in terms of relevancy. To check the relevancy of knowledge, two different forms of TF-IDF are used. In the first form, the score of TF-IDF has been calculated without considering the common vocabularies used in the knowledge item and the given query. The value achieved from this form is called "**Knowledge Weight (KW)**" and shows how much information is utilized in a particular knowledge item. In the second form, the TF-IDF score has been computed with consideration of the common vocabularies used in the knowledge item and the given query. The value of the second form is called "**Knowledge Relevancy Score (KRS)**". It shows whether the the knowledge item explains terms of the query or not. Using these two scores helps to select the most relevant knowledge. The knowledge item will be ranked on relevancy using the KRS. In cases where the KRS for knowledge item is the same, the KW will be used to select the most relevant knowledge. The following discusses how to compute KW and KRS.

TF-IDF represents the importance of a a term used in a document. Here each document is an abstract of an article (ab) extracted from the PubMed KS. This ab exists in a set of related abstracts $(aSet)$ extracted for a given query. Using the statistical formula of TD-IDF helps to understand to what extent an abstract is relevant and contains useful information. The following explains the TF-IDF as it has been modified for this research.

The TF-IDF contains two parts: TF, and IDF. TF is represented by $tf(t, ab)$. The number of times that term t occurs in the abstract ab shows $freq_t$. There are a range of ways to calculate TF. Some of the most common formulas are:

Boolean Formula:

$$tf(t, ab) = \begin{cases} 1, & \text{if } t \text{ occurs in } \ abs \\ 0, & \text{otherwise.} \end{cases} \tag{5.11}$$

Logarithmic Formula:

$$tf(t, ab) = \begin{cases} 0, & \text{if } freq_t = 0 \\ 1 + \log(freq_t), & \text{otherwise.} \end{cases} \tag{5.12}$$

Completed Formula (to prevent a bias):

$$tf(t, ab) = 0.5 + 0.5 \cdot \frac{freq_t}{\max\{freq_{t'}\}} \tag{5.13}$$

where $\max\{freq_{t'}\}$ is the maximum number of TF for a term in the abstract.

The IDF $(idf(t, aSet))$ checks whether the term in all abstracts within the set is common term or not (in the sense of having the same meaning). To measure IDF for a term, a logarithmic formula is applied with a division of the number of all abstracts in the set $|aSet|$ per number of abstracts that contain the term $|\{ab \in aSet : t \in ab\}|$. If there is no document containing the term, the division will be to divide-by-zero. In this case, the denominator will be added to by one. So,

$$idf(t, aSet) = \begin{cases} log\dfrac{|aSet|}{|\{ab \in aSet : t \in ab\}|}, & \text{if } |\{ab \in Aset : t \in ab\}| \neq 0 \\ log\dfrac{|aSet|}{1 + |\{ab \in aSet : t \in ab\}|}, & \text{otherwise.} \end{cases} \tag{5.14}$$

Then TF-IDF is calculated as

$$tfidf(t, ab, aSet) = tf(t, ab).idf(t, aSet). \tag{5.15}$$

a) Calculating KW

The KW can be computed by summing the total score of TF-IDFs of all terms used in a particular abstract ab. The following equation calculates the KW:

$$KW = \sum_{t \in ab} tfidf(t, ab, aSet) \tag{5.16}$$

b) Calculating KRS

The KRS considers common terms in abstract ab and the given query q. The idea is to check how close knowledge is to the query. In other words, to what extent are the terms used in the query also used in the knowledge item. The following equation computes the KRS:

$$KRS = \sum_{t \in ab \cap q} tfidf(t, ab, aSet) \tag{5.17}$$

The relevancy knowledge QM has been applied to the abstract of each knowledge item (i.e., article). Algorithm 1 represents the process of evaluating relevancy knowledge QM. The algorithm takes all knowledge abstracts and a query as inputs and generates a list of Relevancy Scores ($RelS$) for the knowledge items as output. It extracts a $words$ set of a knowledge abstract which contains every word of the knowledge abstract(w) along with its number of occurrences in the knowledge abstract (c). The process of extracting $words$ sets will be applied to all of the knowledge abstracts and stored in the $ListOfWords$ (Lines 3-11). For each word (w) in each $words$ set, the number of knowledge abstracts that contain the word (dc) will be calculated and added to the word's information (Lines 12-15). Before calculating the KW and KRS scores, the terms of the query will be extracted and stored in $queryTerms$ (Line 16). To calculate KW and KRS, the $tfidf$ score of each word will be added to the KW. If the word is in the $queryTerms$, the $tfidf$ score of that word will be added to the KRS (Lines 19-23). When the KW and KRS scores are calculated for a knowledge abstract, it be added to the $RelS$ list (Line 24). The process of KW and KRS calculation will continue until there is no knowledge abstract in the list which has no $RelS$ score. The algorithm finally returns the updated $RelS$ (Line 25).

Algorithm 1: Calculating relevancy of knowledge

```
   input  : Knowledge abstracts(K_abstracts), Query(q)
   output : List < KW, KRS > (RelS)
1  RelS ← ∅;
2  ListOfWords ← ∅;
3  for each a ∈ K_abstracts do
4      List < word(w), count(c), documentCount(dc) > words ← ∅;
5      abstractWords ← a.StringTokenizerBy(' ') ;
6      for each w ∈ abstractWords do
7          if w ∉ words then
8              words.add(w, 1, 1);
9          else
10             words(indexOf(w)).increaseCount
11         ListOfWords ← add words ;
12 for each words ∈ listOfWords do
13     for each w ∈ words do
14         n ← |words.contains(w)| ;
15         w.update(dc, n) ;
16 queryTerms ← q.StringTokenizerBy(' ') ;
17 for each words ∈ listOfWords do
18     KW, KRS ← ∅ ;
19     for each w ∈ words do
20         tfidf = (1 + log_10 (c)) · (log_10 (|K_abstracts| / dc)) ;
21         kw ← add tfidf ;
22         if w ∈ queryTerms then
23             KRS ← add tfidf;
24     RelS ← add < KW, KRS > ;
25 return RelS
```

Example 5. Consider the example shown in Figure 5.5 to get a better understanding of the calculation of the relevancy knowledge QM. The figure shows an abstract of the first clinical knowledge item, which is extracted for a query on “Tuberculous Arthritis”. The right part of the figure shows abstract terms with their frequencies. In this example, the goal is to compute the KW and KRS for this knowledge item. Table 5.3 presents the TF-IDF score for each term used in this abstract. To compute the IDF, the number of extracted knowledge item for a given query is 18 as the PubMed search engine gives the same number of knowledge for the given query. In this case, the KW is about 56.54. If the query is about “Tuberculosis arthritis”, the KRS will be checked for “Tuberculosis” and “Arthritis” terms, which are common in both query and text. Therefore, the KRS is about 0.17.

The proposed approach has used a simple information retrieval technique (i.e., TF-IDF) to measure the relevancy of knowledge item. It is important to note that some other sophisticated techniques for stop word removal and lemmatization tasks have not currently been considered in the assessing process. This could be changed in the future as KQA is a modular system. In fact, this system is a “proof of concept”, so, the proposed system does not optimize any module at this stage. In future, the filtering techniques will be added to the system to improve the assessment of relevancy.

Tuberculosis TB is common in countries constituting endemic areas like Morocco, spinal sites represents half of osteo-articular locations, while peripheral locations in the limbs are rare. The authors relate in this observation the case of a particular location of tuberculosis arthritis. It is osteoarthritis of the metatarsophalangeal joint of the 2(nd) ray of the foot. Clinical signs were characterized by a moderately painful swelling of the dorsum of the foot with slow evolution. The definitive diagnosis was histologically obtained. Clinical cure was achieved after 09 months of medical treatment.

1. tuberculosis : 2
2. tb
3. is
4. common : 1
5. in : 3
6. countries : 1
7. constituting : 1
8. endemic : 1
9. areas : 1
10. like : 1
11. morocco : 1
12. spinal : 1
13. sites : 1
14. represents : 1
15. half : 1
16. of : 9
17. osteo-articular : 1
18. locations : 2
19. while : 1
20. peripheral : 1
21. the : 9
22. limbs : 1
23. are : 1
24. rare : 1
25. authors : 1
26. relate : 1
27. this : 1
28. observation : 1
29. case : 1
30. a : 2
31. particular : 1
32. location : 1
33. arthritis : 1
34. it : 1
35. ....

Figure 5.5: A sample knowledge abstract with term frequencies

Table 5.3: TF-IDF score for sample abstract shown in Figure 5.5

Term	$freq_t$	$\lvert\{ab \in aSet : t \in ab\}\rvert$	**TF-IDF score**
Tuberculosis	2	17	0.03229622702614305
Tb	2	6	0.6532125137753437
Is	2	11	0.2782640612157619
Common	1	5	0.5563025007672873
In	3	16	0.07555847813955155
Countries	1	2	0.9542425094393249
Constituting	1	1	1.255272505103306
Endemic	1	4	0.6532125137753437
Areas	1	2	0.9542425094393249
Like	1	1	1.255272505103306
Morocco	1	1	1.255272505103306
Spinal	1	1	1.255272505103306
Represents	1	1	1.255272505103306

Half	1	1	1.255272505103306
Of	9	17	0.048511302552084
Osteo-articular	1	1	1.255272505103306
Locations	2	1	1.6331471818716692
While	1	1	1.255272505103306
Peripheral	1	2	0.9542425094393249
The	9	16	0.09996443383172181
Limbs	1	1	1.255272505103306
Are	1	7	0.41017446508904926
Rare	1	4	0.6532125137753437
Authors	1	1	1.255272505103306
Relate	1	1	1.255272505103306
This	1	8	0.3521825181113625
Observation	1	1	1.255272505103306
Case	1	3	0.7781512503836436
A	2	16	0.06655096605791819
Particular	1	1	1.255272505103306
Location	1	1	1.255272505103306
Arthritis	1	15	0.07918124604762482
It	1	2	0.9542425094393249
Osteoarthritis	1	2	0.9542425094393249
Metatarsophalangeal	1	1	1.255272505103306
Joint	1	10	0.25527250510330607
2nd	1	1	1.255272505103306
Ray	1	1	1.255272505103306
Foot	2	1	1.6331471818716692
Clinical	2	6	0.6207490639591157
Signs	1	2	0.9542425094393249
Were	1	11	0.21387981994508107
Characterized	1	1	1.255272505103306
By	1	4	0.6532125137753437
Moderately	1	1	1.255272505103306
Painful	1	1	1.255272505103306
Swelling	1	2	0.9542425094393249
Dorsum	1	1	1.255272505103306
With	1	15	0.07918124604762482
Slow	1	1	1.255272505103306
Evolution	1	1	1.255272505103306
Definitive	1	1	1.255272505103306
Diagnosis	1	8	0.3521825181113625
Was	2	12	0.22910001000567795

Histologically	1	1	1.255272505103306
Obtained	1	1	1.255272505103306
Cure	1	2	0.9542425094393249
Achieved	1	1	1.255272505103306
After	1	5	0.5563025007672873
09	1	2	0.9542425094393249
Months	1	4	0.6532125137753437
Medical	1	3	0.7781512503836436
Treatment	1	7	0.41017446508904926
KW			56.540300489100865
KRS			0.17569543548298627

Accuracy

This knowledge QM is to discover whether knowledge is accurate enough to support the user query. To evaluate this knowledge QM, we used an ontology comparison mechanism to understand which knowledge is more accurate compared with others. As previously mentioned, in this research, the knowledge (i.e., articles) obtained from the KS has been transformed into ontological structures. Consider again the framework of KQA shown in Figure 5.2. As seen in the figure, the knowledge items will be compared with the main knowledge item. Any knowledge which has been compared with the main knowledge item obtains a particular score. This score indicates that how similar the knowledge item is to the main one. In the field of ontology matching, such a comparison demonstrate the concept of accuracy for a particular knowledge item.

In the following sections, the similarity factors for comparing ontologies based on Lexical Similarity(LS) and Semantic Similarity(SS) of ontologies are defined. The LS refers to the string similarity of terms, while the SS refers to the hierarchical and relationship similarity.

a) Calculating LS

In order to assess the similarity between two terms (which are in string formats), the Edit Distance (ED) formulated by (Levenshtein, 1966) is used. This formula measures the minimum number of token insertions, deletions, and substitutions required to transform a string of a term into another string. Algorithm 2 shows the process for calculating the ED. The algorithm takes two terms (i.e. words) as inputs and returns an ED score for those terms as an output. Firstly, a two dimensional array is created for recording the ED score by checking letters for each term. The number of rows for the query is equal to the number of letters of term 1 (t_1) plus 1 and the number of columns is equal to the number of letters of term 2 (t_2) plus 1. The numbers of rows and columns is increased by 1 as a space is inserted at the beginning of the word for the ED calculation (Lines 1-3). Cells of the first row and first column in the array get the score equal to the index of a particular column for the cell in the first row and the index of a particular row for the cell in first column respectively. The numbers show how many changes are needed to change an empty string to a term from the first letter to the current letter (Line 4-7). Consider Figure 5.6, as an example. The number 5 for letter 'r' in the first row shows that there needs to be 5 changes to modify an empty string to a term with the letters "Tuber". For each letter and term with the sequence of letters of t_1 and t_2, the ED score will be calculated and stored in the array. If two letters in the terms are equal, the ED in the array by index of [current row - 1][current column-1] will be the ED score of the ED for letters in [current row][current column] position (Lines 9-10). To clarify, consider Figure 5.6. If we wish to calculate ED 'u' as a second letter of word 1 and as a seventh letter in word 2, the "current row" is 2 and "current column" is 7, So, the $ED[2][7]$ is equal to $ED[1][6]$. In the case that the letters are not equal, the ED score will be calculated based on the previous ED scores in the array in [current row][current column-1], [current row - 1][current column] and [current row - 1][current column-1] positions. Therefore, the ED score is equal to the lowest ED score among those ED scores plus 1. The process of calculating ED scores and storing them in the array will continue until it reaches the end of both terms (Line 8-12). Finally, the last ED score in the array ($ED[m][n]$) will be returned as output to show how many changes are required to modify one term to another (Line 13).

Algorithm 2: ED calculation

input : $t_1,\ and\ t_2\ as\ terms$
output : ED

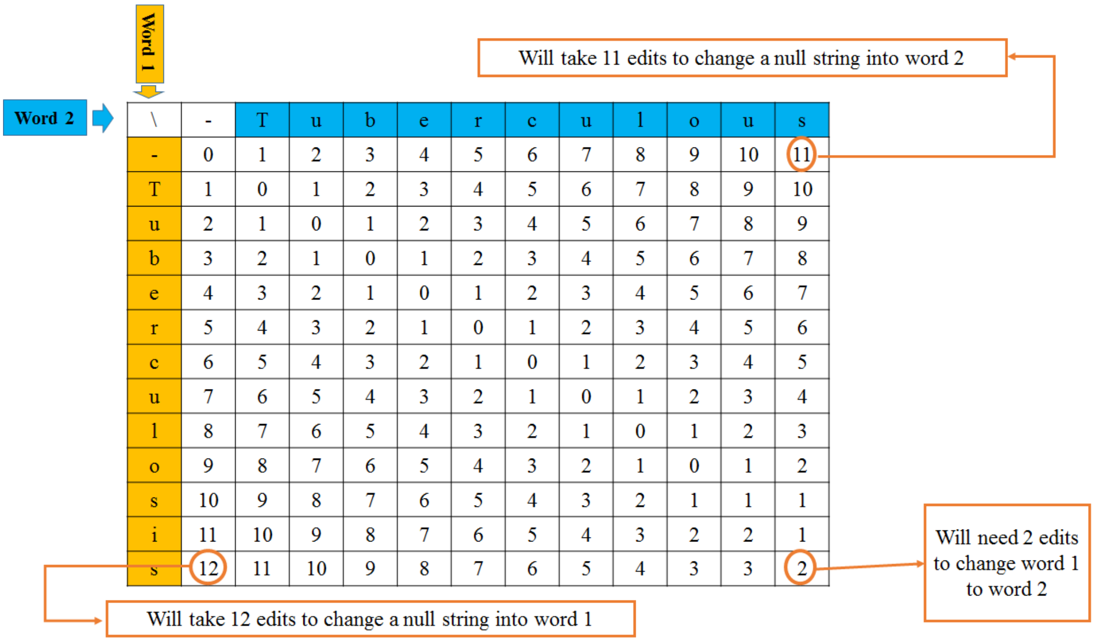
1 $m \leftarrow t_1.length$;
2 $n \leftarrow t_2.length$;
3 $ED[1,m][1,n] \leftarrow \varnothing$;
4 **for** *each* $i \in [1,m]$ **do**
5     $ED[i][0] = i$;
6 **for** *each* $j \in [1,n]$ **do**
7     $ED[i][0] = i$;
8 **for** *each* $i \in [0,m]\ and\ j \in [1,n]$ **do**
9   **if** $t_1[i-1] == t_2[j-1]$ **then**
10         $ED[i][j] = ED[i-1][j-1]$;
11   **else**
12         $ED[i][j] = 1 + \min\{ED[i][j-1], ED[i-1][j], ED[i-1][j-1]\}$
13 return $ED[m][n]$

Based on the ED formula, we have proposed a LS measurement for comparing and evaluating the similarity between two terms. The LS can be calculated using Equation (5.18).

$$LS(t_n, t_m) = \begin{cases} \dfrac{\min\{|t_n|, |t_m|\} - ED(t_n, t_m)}{\min\{|t_n|, |t_m|\}}, & \text{if } (\min\{|t_n|, |t_m|\} - ED(t_n, t_m) \neq 0) \\ 0, & \text{otherwise.} \end{cases} \tag{5.18}$$

The LS returns a similarity value between 0 and 1, where 0 refers to a bad match and 1 to a perfect match. The LS shows a bad match when the ED score is equal to the number of letters for the shortest term. In this case, all of the letters in the shortest term need to be changed to become like the other term which is not a good match.

Example 6. Figure 5.6 illustrates how to compute the ED for a particular term. In this figure, the ED between the two strings “Tuberculous” and “Tuberculosis” equals 2, ED(“Tuberculous”,“Tuberculosis”) = 2, because one insertion and one substitution operation transform the “Tuberculous” into “Tuberculosis”. To compute the LS for the terms “Tuberculous” and “Tuberculosis” LS(“Tuberculous”, “Tuberculosis”) is equal to $\frac{9}{11}$.



\	-	T	u	b	e	r	c	u	l	o	u	s
-	0	1	2	3	4	5	6	7	8	9	10	11
T	1	0	1	2	3	4	5	6	7	8	9	10
u	2	1	0	1	2	3	4	5	6	7	8	9
b	3	2	1	0	1	2	3	4	5	6	7	8
e	4	3	2	1	0	1	2	3	4	5	6	7
r	5	4	3	2	1	0	1	2	3	4	5	6
c	6	5	4	3	2	1	0	1	2	3	4	5
u	7	6	5	4	3	2	1	0	1	2	3	4
l	8	7	6	5	4	3	2	1	0	1	2	3
o	9	8	7	6	5	4	3	2	1	0	1	2
s	10	9	8	7	6	5	4	3	2	1	1	1
i	11	10	9	8	7	6	5	4	3	2	2	1
s	12	11	10	9	8	7	6	5	4	3	3	2

Figure 5.6: A sample example for calculating ED for two terms

To measures and summarize the LS of two sets of terms T_1, T_2 of two ontologies O_1, O_2, we have proposed Equation (5.19) that measures the averaged LS ($\overline{LS}(T_1,T_2)$) as follows:

$$\overline{LS}(T_1,T_2) = \frac{1}{|T_1|} \sum\nolimits_{t_n \in T_1 \wedge t_m \in T_2} \max\{LS(t_n,t_m)\} \tag{5.19}$$

Equation (5.19) calculates each term of T_1 by each term in T_2. The maximum amount of LS for a term in T_1 to compare with a term T_2 will be added to the sum of LS for calculating $\overline{LS}$. As mentioned before, each set of T contains two parts: T^C for concepts and T^R for relationships. To calculate $\overline{LS}$ we consider both parts separately. $\overline{LS}(T_1,T_2)$ will be calculated in two ways and will be summed up at the end. Therefore, $\overline{LS}(T_1,T_2) = \overline{LS}(T_1^C,T_2^C) + \overline{LS}(T_1^R,T_2^R)$. Technically, the LS indicates to what extent terms in set T_1 (the origin) are covered by T_2 (the destination). It is clear that the $\overline{LS}(T_1,T_2)$ is quite different from $\overline{LS}(T_2,T_1)$. E.g., when T_2 contains all the strings of

T_1 with some other terms $\overline{LS}(T_1, T_2) = 1$. However, $\overline{LS}(T_2, T_1)$ might be zero.

Algorithm 3 shows how the system computes the $\overline{LS}$. This algorithm takes sets of terms from two ontologies (T_1, T_2) as inputs and returns a Lexical Similarity Score ($\overline{LS}$) as an output. The algorithm calculates LS for each term in T_1 with terms in T_2 one by one. The algorithm then selects the maximum number of LS for the term and adds it to the $sumLS$. This algorithm takes advantage of the ED score. It is linked to Algorithm 2 in its calculation of ED for terms in T_1 and T_2(Lines 4-11). At the end, the average number for LS ($\overline{LS}$) will be returned as an Lexical Similarity score for the two sets of terms.

Algorithm 3: calculating $\overline{LS}$

input : $T_1,\ T_2$
output : $\overline{LS}$

1 $m \leftarrow |T_1|$;
2 $n \leftarrow |T_2|$;
3 $sumLS \leftarrow 0$;
4 **for** *each* $t_k | k \in [0, m],\ t_k \in T_1$ **do**
5     $maxLS \leftarrow 0$;
6   **for** *each* $t_l | l \in [0, n],\ t_l \in T_2$ **do**
7         $minLength \leftarrow \min\{|t_k|, |t_l|\}$;
8         $ed \leftarrow ED(t_k, t_l)$;
9         $LS \leftarrow \max\left\{0, \dfrac{minLength - ed}{minLength}\right\}$;
10         $maxLS \leftarrow \max\{maxLS, LS\}$;
11     $sumLS \leftarrow add\ maxLS$;
12 return $\frac{sumLS}{m}$

The degree of similarity for LS may sometimes be tricky. Sometimes, two particular terms are lexically similar, but they are semantically different. For example, there is no meaningful link between “towel” and “tower”. Hence, we need to check the semantic similarity of the knowledge item to understand which concepts and relationships are much more similar. The following explains the SS measurement.

b) Calculating SS

In order to measure the SS, we are going to compare the semantic structures of the ontologies of the extracted knowledge. These ontologies are different in concept. In KQA, the SS of ontologies is evaluated based on the CHs of ontologies and relationship similarities. To do this, it is necessary to compare the similarity of class hierarchies to check the superclass-subclass relationships among classes of the ontologies. We then define sound measurements to check relationship similarities. For relationship similarity, relationships that have no "Has_subclass" and "Has_individual" relationships will be considered.

To compute the similarity of class hierarchies, the CH of each ontology will be compared with the CH of the main ontology (See Section 5.4.1). Assume there are two ontologies O_1 and O_2. To compare the CHs of these two ontologies, we need to check the position of each class in the CH. When all of the results of each class are calculated, the summation of them is the Class Hierarchy Similarity (CHS) score that can be used for calculating SS. Assume that we have a term $t \in T_1^C \cap T_2^C$ that refers to two classes c_1, c_2 from two different class hierarchies of O_1 and O_2.

The KQA approach considers individuals first. It then considers the class information of each individual where an individual belongs to the Lowest Level Class (LLC) in the CH. Namely, the approach only assumes the classes that have "Has_individual" relationship as corresponding to individuals. Then the related computations will be applied using these classes. For example in Figure 5.7, to evaluate the Class Position (CP) of "Knee Swelling" in the ontology O_1, the approach considers the nearest class (i.e. LLC), which is c_5. As seen in the figure, the label of c_5 is "Joint Swelling".

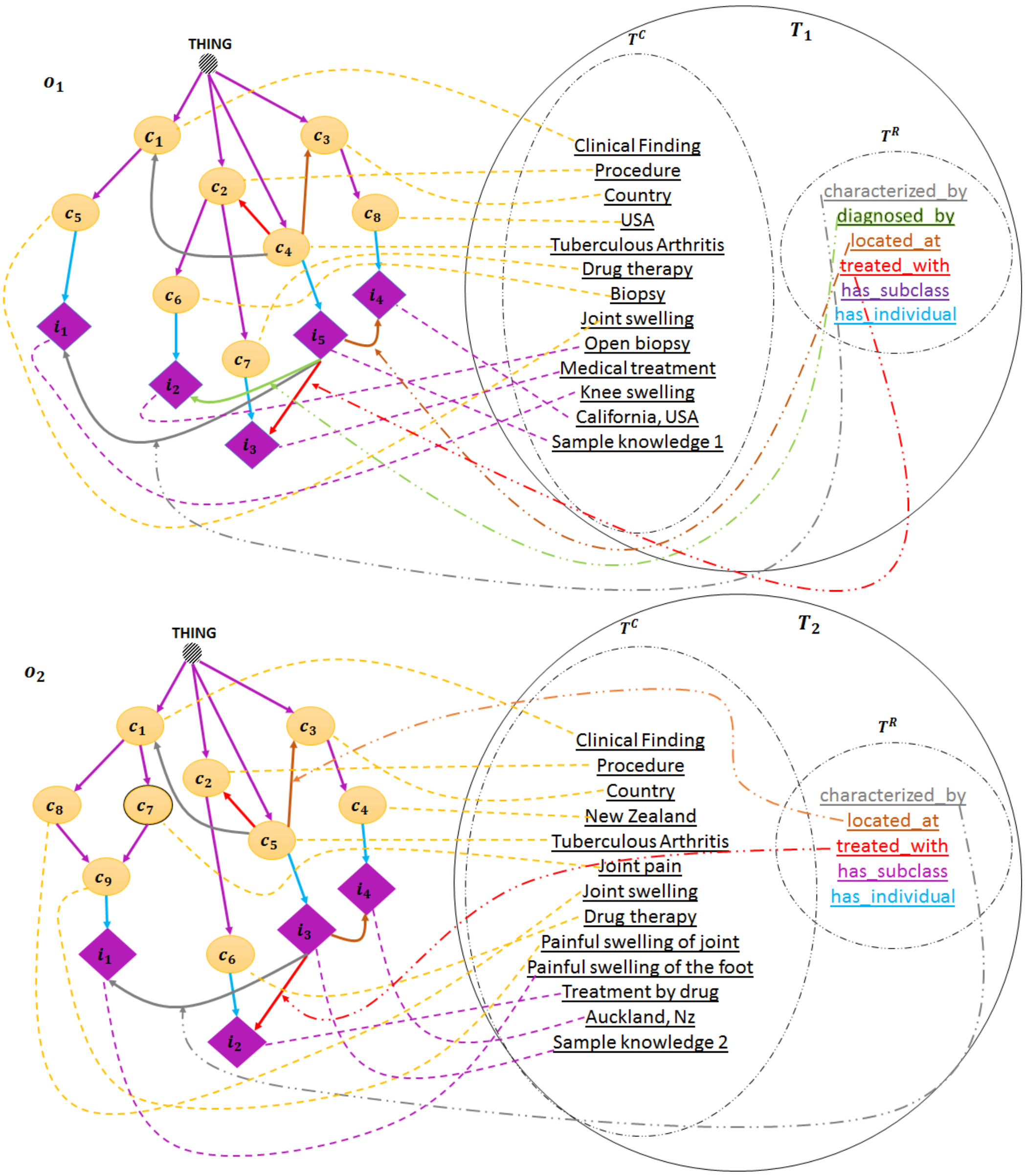


Figure 5.7: Two Example Ontologies O_1,O_2

The CP of a class $c_n(CP(c_n, CH))$ will be calculated by Equation (5.24). The class with all its superclasses and subclasses need to be considered.

$$CP(c_n, CH) = \{Super(c_n, CH) \cup Sub(c_n, CH) \cup c_n\} \tag{5.20}$$

where $Super(c_n, CH)$ are the superclasses of c_n in $CH$and $Sub(c_n, CH)$ are the subclasses of c_n in CH.

The CHS between CH_1 and CH_2 for the two ontologies of O_1 and O_2 may then be calculated through CP of classes in CH_1 and CH_2. Equation (5.21) shows how to compute the CHS between CH_1 and CH_2 for a class c_n.

$$CHS_{c_n}(CH_1, CH_2) = \frac{|CP(c_n, CH_1) \cap CP(c_n, CH_2)|}{|CP(c_n, CH_1) \cup CP(c_n, CH_2)|} \tag{5.21}$$

In this thesis, we have calculated the subscription of two CPs when there are equal classes among them. Apart from structure and level of granularity of class in CHS, two classes are equal when they have same term as their name (i.e. The classes should show the same concept).

In some cases, the class c_n is in CH_1, but not in CH_2. Namely, the c_n does not exist in CH_2. In this case, when comparing the two hierarchies CH_1, CH_2, all of the common classes in $CP(c_n, CH1)$ and CH_2 will be used to calculate CHS for c_n. The common class which can give the highest score for $CHS_{c_n}(CH_1, CH_2)$ will be selected. Equation (5.22) shows how this calculation works.

$$CHS_{c_n}(CH_1, CH_2) = \max \left\{ \frac{|CP(c_n, CH_1) \cap CP(c_m, CH_2)|}{|CP(c_n, CH_1) \cup CP(c_m, CH_2)|} \right\} \tag{5.22}$$

where $c_m \in CP(c_n, CH_1)$.

The SS for CH of the two ontologies O_1 and O_2 can be calculated by averaging all

CHS of the classes. The averaged similarity $\overline{CHS}$ between two class hierarchies CH_1 and CH_2 can be defined through Equation (5.23).

$$\overline{CHS}(CH_1, CH_2) = \frac{\sum\limits_{c_n \in CH_1} CHS_{c_n}(CH_1, CH_2)}{|CH_1|} \tag{5.23}$$

Example 7. Figure 5.7 shows two different ontologies. The CHS for the class "Joint swelling" (c_5) is determined by

$$CP('joint\,swelling', CH_1) = \{'Joint\,swelling', 'Clinical\,Finding'\}$$

and

$$CP('Joint\,swelling', CH_2) =$$
$$\{'Joint\,swelling', 'Clinical\,Finding', 'Painful\,swelling\,of\,joint'\}$$

resulting in $CHS_{'Joint\,swelling'}(CH_1, CH_2) = \frac{2}{3}$. When we consider the class of "Biopsy" (c_6), which is only exist in CH_1, we use the second formula to calculate the CHS. The CP for the the class of "Biopsy" in CH_1 is $CP('Biopsy', CH_1) = 'Procedure', 'Biopsy'$. The KQA looks for common classes between $CP('Biopsy', CH_1)$ and CH_2. Here, the class referred to as "Procedure" is the only class which exists in CH_2. So, it will use this to calculate $CHS_{'Biopsy'}(CH_1, CH_2)$. The $CP('Procedure', CH_2)$ is equal to $\{'Procedure', 'Drugtherapy'\}$ and, thus, $CHS_{'Biopsy'}(CH_1, CH_2) = \frac{1}{3}$. Sometimes, we might have more than one common class between $CP(c_n, CH_1)$ and CH_2 in the case of $c_n \notin CH_2$. As mentioned in Equation (5.22), in this case, the best match resulting from the CHS calculation will be selected as the input for $\overline{CHS}$.

To compute similarity of relationships, a relationship r is specified by a general $SPO(Subject, Predicate, Object)$ pattern. A relationship r in this pattern describes a triple (D_r, r, R_r) where $D_r, R_r \in C$. Usually describing a relationship in an ontology starts with a domain D_r as the origin of the relationship and ends with a range R_r as the destination of the relationship. Relationship Similarity (RS) of two relationships R_1, R_2 is based on the similarity between the domains and ranges of the relationships. If there is no similarity in the domains and ranges of the relationships, the RS score for those relationships will be zero.

To calculate RS, the KQA approach only considers the given class c_n in the domain or range of a relationship along with its superclasses. As mentioned before, the approach considers the relationships available to the individuals. In order to compute the RS, the approach uses the LLC to the domain and range of each relationship. As seen in Figure 5.7, in O_2, the individual number 3 (i_3) has been connected to the individual number 2 (i_2) through the relation "treated_with". To compute RS, the c_5 class has been considered as domain (this class in the nearest class to i_3 and it is connected to i_3 through the "Has_individual" relationship) . Furthermore, the c_6 class has been used as the range (this class in the nearest class to i_2 and it is connected to i_2 through the "has_individual" relationship).

The similarity between two classes (CS) is calculated as follow:

$$CS(c_n, c_m) = \frac{|Super(c_n) \cap Super(c_m) \cap c_n \cap c_m|}{|Super(c_n) \cup Super(c_m) \cup c_n \cup c_m|} \tag{5.24}$$

where $c_n \in CH_1$ and $c_m \in CH_2$.

Based on the definition of CS, RS is calculated by Equation (5.25).

$$RS(r_n, r_m) = \sqrt{CS(D_{r_n}, D_{r_m}) \cdot CS(R_{r_n}, R_{r_m})} \tag{5.25}$$

where $r_n \in R_1$ and $r_m \in R_2$ are relationships for O_1 and O_2, correspondingly.

The averaged $RS(\overline{RS})$ for all of the relationships in O_1 and O_2 is then defined by:

$$\overline{RS}(R_1, R_2) = \frac{\sum_{r_n \in R_1} RS(r_n, r_m)}{|R_1|} \tag{5.26}$$

where $r_m \in R_2$.

Algorithm 4 shows how Semantic Similarity (SS) is calculated in this approach. The algorithm applies the mechanisms of $\overline{CHS}$ and $\overline{RS}$ measurement to calculate SS. In this algorithm classes which have "Has_individual" relationships (i.e. contain individuals in LLC) will be extracted and stored. Classes for the ontological structure of the main knowledge item (o_1) will be stored in $mainC$ and classes from an ontological structure of a knowledge item (o_n) that will be compared with the main knowledge item will be stored in $tempC$ (Lines 6-11). In the next step, the relationships of o_1 and o_n will be extracted and stored in $mainRelationships$ and $tempRelationships$ respectively. As mentioned earlier, relationships should not be "Has_subclass" or "Has_individual" relationships (Lines 12-24). For each class of $mainC$ the CHS is calculated considering its equal class in $tempC$. Then, the average CHS ($\overline{CHS}$) will be calculated to show the class hierarchy similarity score of o_1 (main ontology) with o_n (Lines 25-28). For each relation of $mainRelationships$ the RS will be calculated considering the same relation in $tempRelationships$ and added to the RS_{sum}. The average of RS ($\overline{RS}$) will be recorded as Relationship Similarity for o_1 and o_n (Lines 29-32). Lastly $\overline{CHS}$ and $\overline{RS}$ will be recorded for SS (Line 33). At the end, when the SS is calculated for all o_n with o_1, SS set will be returned as an output (Line 34).

Example 8. Consider again Figure 5.7 for computing RS. We assume one relationship r_1 in R_1, referenced by the term "characterized_by" and specifying the domain and range corresponding to ("Tuberculous Arthritis", "Joint swelling"). In the R_2, the same term may refer to r_2, with domain and range corresponding to ("Tuberculous Arthritis", "Painful swelling of joint"). Computing CS for the classes referred as "Tuberculous Arthritis" in O_1 and O_2 results in 1 . The CS between the classes referred as "Joint swelling" in O_1 and "Painful swelling of joint" in O_2 also returns $\frac{1}{3}$. Thus, the RS for the term "characterized_by" is $\sqrt{1 \times \frac{1}{3}} = \sqrt{\frac{1}{3}}$.

Algorithm 4: Calculating SS

```
input   : KnowledgeOntologties(O)
output  : List < CHS‾, RS‾ > SemanticSimilarity(SS)
mainC ← ∅;
List < RelationshipName(RN), D, R > mainRelationships;
for each o_n ∈ O do
    tempC ← ∅;
    List < RN, D, R > tempRelationships;
    for each c ∈ o_n.C do
        if c.contains('Has_induvidual' relationship) then
            if o equals o_1 then
                mainC ← add(c);
            else
                tempC ← add(c);
    for each relation ∈ o_i.R do
        RN ← relation;
        if RN! = ('Has_individual' and 'Has_subclass' relationships) then
            if o equals o_1 then
                if (!mainRelationships.contains(RN)) then
                    mainRelationships ← add < RN, d(RN), r(RN) >;
                else
                    mainRelationships.indexOf(RN).update(d(RN), r(RN));
            else
                if (!tempRelationships.contains(RN)) then
                    tempRelationships ← add < RN, d(RN), r(RN) >;
                else
                    tempRelationships.indexOf(RN).update(d(RN), r(RN));
    for each c ∈ mainC do
        CHS ← calculate CHS(o_1.CH, o_n.CH);
        CHS_sum ← add CHS;
    CHS‾ ← (1 / |mainC|) · CHS_sum;
    for each r ∈ mainRelationships do
        RS ← calculate RS(r|r ∈ o_1.R, r|r ∈ o_n.R);
        RS_sum ← add RS;
    RS‾ ← (1 / |mainRelationships|) · RS_sum;
    SS ← add(CHS‾, RS‾);
return SS
```

5.5 Calculating Knowledge Quality Indicator (KQI)

After evaluating the intrinsic and contextual knowledge QMs, a KQI will be assigned to any knowledge extracted from the KSs (e.g. PubMed). In this thesis, the KQI indicates the quality of extracted knowledge. The KQA sorts the evaluated knowledge from the highest KQI score to the lowest one. It then provides health experts with the confidence in appropriate knowledge for better decisions.

This section focuses on computing the KQI by two different means; linear and weighted. The KQI has been evaluated considering the knowledge QMs scores of the given knowledge. Note that the knowledge QM scores of a particular knowledge item can be stored in a V set. Computing the KQI score using linear approach is as follows:

$$KQI_{Linear} = \sum_{k=0}^{n-1} v_k \tag{5.27}$$

where n is the number of knowledge QMs applied to the knowledge item. The v_k is a score for a knowledge QM calculated for a knowledge item.

If the average ratings of knowledge QMs (refer to Table 5.2) are considered weights of knowledge QMs (stored in a set W), then, the $KQI_{Weighted}$ can be computed through the following equation:

$$KQI_{Weighted} = \frac{\sum_{k=0}^{n-1} w_k \cdot v_k}{\sum_{k=0}^{n-1} w_k} \tag{5.28}$$

where n is the number of QMs applied to the knowledge item. The w_k is the average rating of a knowledge QM.

In the end, the knowledge will be ranked based on the KQI score achieved by the above equations. As explained in this chapter, Age, Citation, Structure, Relevancy and Accuracy have been used to assess quality of knowledge. So, the number of knowledge QMs (n) is 5. The V set contains five values for each knowledge QM (See below).

$$V = \{v_0, v_1, v_2, v_3, v_4\}$$

where $v_0 = v_{Age}, v_1 = v_{Citation}, v_2 = v_{Structure}, v_3 = v_{Relevancy}, v_4 = v_{Accuracy}$. Moreover, W set has weights of each knowledge QM received from questionnaire.

$$W = \{w_0, w_1, w_2, w_3, w_4\}$$

where $w_0 = w_{Age}, w_1 = w_{Citation}, w_2 = w_{Structure}, w_3 = w_{Relevancy}, w_4 = w_{Accuracy}$.

Example 9. Imagine the V and W sets for a knowledge item for Age, Citation, Structure, Relevancy and Accuracy is:

$$V = \{3, 1, 1.9, 0.17, 1\}$$
$$W = \{3.8, 3.6, 3.4, 3.9, 4.7\}$$

Hence, KQI_{Linear} and $KQI_{Weighted}$ are as bellow:

$$KQI_{Linear} = 7.07$$
$$KQI_{Weighted} = 26.823$$

Note that this approach can be extended with additional knowledge QMs that will extend the W and V sets. In other meaning, the KQA approach is modular, so, each knowledge QM is added to the approach as a module. Therefore, KQA can include the additional knowledge QMs as different modules. For example, if reliability knowledge QM is added to the approach, the number of knowledge QMs will be modified to 6 and V and W sets will include the value and weight of reliability.

5.6 Chapter Summary

This chapter discusses the measurements of knowledge QMs for assessing the quality of extracted knowledge from KSs (e.g. PubMed) for use in CDSSs. In this chapter, knowledge QMs have been formally defined and modelled. Calculating the KQI as an indicator of the quality of knowledge was explained to be assigned to the knowledge item for future use.

Chapter 6

Evaluation

6.1 Introduction

The aim of this chapter is to assess and explain the results (i.e., discovered high quality knowledge) through employing the knowledge QMs. This chapter also aims to demonstrate the performance of the KQA in detecting high quality knowledge. The experiments have been inspired by real world example mentioned in Chapter 1 (for "Tuberculosis Arthritis"). The experiments tested the knowledge QMs with real-world knowledge to show the KQA is able to detect high quality knowledge to support KA for CDSSs. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

This chapter contains three main phases which are shown in Figure 6.1. In the first phase, the related knowledge is extracted from the KS (PubMed) and transformed into ontological structures. Then, characteristics of the ontologies will be explained. In the second phase, the age of knowledge, citation, structure, accuracy and relevancy knowledge QMs are applied to the ontological structure of the knowledge item independently. Evaluated knowledge will be ranked based on the results obtained by each of these knowledge QMs. The knowledge ranking is then compared with the initial rank retrieved from the PubMed search engine. Additionally, in this phase, the KQI will be computed and used for ranking knowledge. In order to validate the approach, in the third phase, a questionnaire has been distributed among health experts to check the quality of knowledge ranked by the KQA.

Spearman's Rank Correlation (p) has been used to quantify and validate the comparison between initial knowledge rank and the rank of knowledge by QMs and KQI. In statistical analysis, the Spearman's Rank Correlation comes up with a number to show how the links between two sets of data is strength. It can take values from the range between -1 and +1. If the value is close to +1, there is a perfect similarity between two sets of data. The value of -1 shows perfect negative similarity. And, zero value for p indicates no similarity between sets of data. Here the data is knowledge rank. Equation (6.1) shows how to calculate the value of Spearman's Rank Correlation:

$$p = 1 - \frac{6 \times \sum d_i^2}{n(n^2 - 1)} \tag{6.1}$$

where d is the difference between ranks and d^2 is a squared value of d. The n is the number of observations. In the thesis, n is number of extracted knowledge.

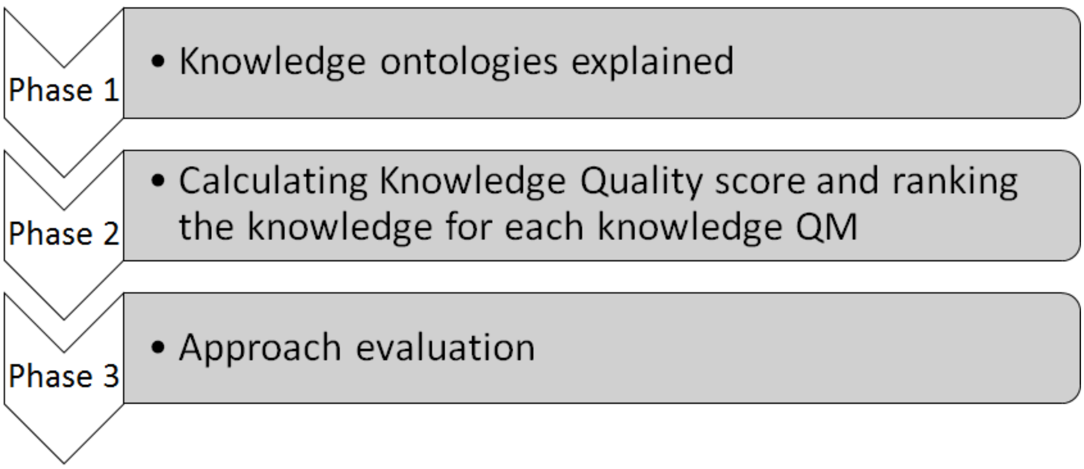


Figure 6.1: Chapter phases overview

6.2 Phase 1

Table 6.1 sets out the extracted knowledge from the PubMed search engine. The knowledge has been retrieved through running a query about “tuberculosis arthritis”. The details of the knowledge item have been extracted from an XML file received from Entrez eutils API. The knowledge extraction was undertaken by a best match search using Title/Abstract and English language filters in PubMed search engine. Figure 4.7 shows a sample of the XML format related to the knowledge. As mentioned in Chapter 4, it is possible to extract useful information related to a particular knowledge item through XML tags provided in the knowledge. For example, “DateCreated” indicates the exact publishing date for the knowledge in PubMed. It is easy to extract the title of a particular knowledge item through the same title tag mentioned in the XML file. The location of the produced knowledge is accessible through the authors’ affiliations. The publication type tag indicates different types of a particular knowledge item such as case studies or articles. The PMID is an information that is accessible from XML files. The abstract and MeSH headings are also information which helps health experts to see the knowledge domains and concepts. Google scholar API also provides the ability to extract the number of citations of a knowledge item. Figure 4.4, represents parts of Google scholar API used in this thesis.

After extracting the related information from XML files through UMLS, SNOMED-CT and MeSH, the ontological structures of knowledge have been prepared using OWL. The ontologies are initially generated by identifying general concepts known as classes. Additionally, individuals (i.e., instances) of classes are extracted from the XML files. The process of creating ontologies using general concepts, relations and annotations has been explained in detail in Chapter 4. Annotations have also been extracted from the XML files, UMLS, SNOMED-CT, and MeSH. In order to use SNOMED-CT and MeSH, we used some APIs and knowledge browsers provide by the National Center for

Biotechnology Information (NCBI).

In this thesis, ontologies are implemented in $Protégé$ ontology editor, the Eclipse Java IDE with 3.20GHz Intel Core i5 processors and 16 GB memory. The implementation process also takes advantage of OWL APIs and APACHE JENA libraries. Table 6.2 presents the basic information for the generated ontologies.

6.3 Phase 2

In this phase, the quality of knowledge has been computed based on the age of knowledge, citation, structure, relevancy and accuracy knowledge QMs. The knowledge is then ranked by knowledge QMs independently and compared with the initial knowledge rank retrieved from the PubMed search engine. Finally, the KQI score for each knowledge item is calculated for the purpose of ranking the knowledge.

6.3.1 Age of knowledge (Age)

As previously discussed in Chapter 5 (Section 5.4.3), the exact age of a particular knowledge is calculated by subtracting the current date from the production date of the knowledge item in the KS. In order to calculate the age of each knowledge item, we assume that the current date is March 2017. Table 6.3 shows the results obtained by applying this knowledge QM. The column of "Initial knowledge rank" indicates the knowledge rank retrieved from the PubMed search engine. The column of "Knowledge rank by the Age knowledge QM" is the result obtained by age of knowledge QM. By considering d^2 column in the Table 6.3, the value of Spearman's Rank Correlation between initial knowledge rank and new rank of knowledge by Age is $p \cong 0.98$. This value indicate that applying age does not have a significant effect on the ranking of the different knowledge by the KQA when compared with the initial knowledge rank retrieved from the PubMed search engine. Figure 6.2 depicts knowledge ranking in the

KQA and the search engine. The result is formed by applying age of knowledge along with initial knowledge rank. As seen in the figure, the initial ranking does not change significantly by applying this knowledge QM.

The results show that a particular knowledge in the PubMed usually ranks based on the date of publication when it extracts on a best match search. The most recent knowledge has a higher place in the ranking list. The results achieved by applying age of knowledge reflects one of the opinions of the surveyed health experts which was "For the age of knowledge, old doesn't mean unusable!" This expression is correct since it is possible that older knowledge is constantly being used as a reference knowledge item in the decision making process, while newer knowledge might be used at a different time for specific reasons. Newer knowledge might contain unhelpful information for the decision making process. Although age of knowledge can be considered a knowledge QM for assessing the quality of knowledge, the quality of knowledge cannot be guaranteed by only considering age of knowledge.

Table 6.1: Knowledge extracted from PubMed search engine for “Tuberculosis arthritis”

K No.	Title	Date Created	Location	Publication type	MeshHeading List	PMID	Citation
K1	Tuberculosis arthritis of the metatarsal phalangeal: a rare location	20/10/2014	Morocco	Case reports / Journal Article	Pathology	25328618	1
K2	Periprosthetic tuberculosis of the knee joint treated with anti-tuberculosis drugs: a case report.	10/02/2014	Turkey	Case reports / Journal Article	Therapeutic/ knee joint/ adverse effects/ drug therapy	24509226	2
K3	Tuberculosis arthritis and tenosynovitis	14/11/2011	Thailand	Journal Article / Review	Diagnosis/ Microbiology/ Diagnostic Imaging	22081281	11
K4	Pulmonary tuberculosis and tuberculous arthritis of knee joint associated with rheumatoid arthritis treated with anti-tumor necrosis factor (TNF)-alpha medication: a case report	29/08/2012	Turkey	Case reports / Journal Article	Adverse effects/ complications/ etiology/ antagonists .& inhibitors	21881984	7
K5	Leuconostoc bacteremia in a patient with amyloidosis secondary to rheumatoid arthritis and tuberculosis arthritis	14/12/2011	South Korea	Case reports / Journal Article	Complications/ Isolated & purification	21597950	7
K6	Tuberculosis in children with congenital immunodeficiency syndrome	02/06/2010	Turkey	Journal Article	Therapeutic use/ Immunocompromised Host/ Complications/ Diagnosis/ Drug therapy	20517730	9
K7	Post-traumatic chylous knee effusion	07/02/2011	Japan	Case reports / Journal Article	Metabolism/ Diagnosis	20303766	3
K8	Cementless total hip arthroplasty for the management of the tuberculosis coxitis	29/12/2009	Turkey	Journal Article	Arthroplasty, Replacement/ Hip Joint/ Surgery	19784661	23
K9	Reactivation of ancient joint tuberculosis of the knee following total knee arthroplasty after 61 years: a case report	27/06/2008	The Netherlands	Case reports / Journal Article	Diagnosis/ etiology/ adverse effects/ Knee joint	18514528	24
K10	Tuberculosis Arthritis: A review of 27 cases	08/03/2007	Saudi Arabia	Journal Article		17344697	23

K11	Septic arthritis in patients with human immunodeficiency virus	13/10/2006	USA	Journal Article	Diagnosis/ microbiology/ complications	16906073	29
K12	Advanced imaging of tuberculosis arthritis.	15/08/2003	USA	Journal Article / Review	Developed countries/ diagnosis	12920652	12
K13	Multifocal tuberculosis presenting with osteoarticular and breast involvement.	24/03/2005	Turkey	Journal Article		12685934	18
K14	Concurrent gout and mycrobacterium tuberculosis arthritis	26/03/1997	USA	Case reports / Journal Article	Complications/ microbiology/ isolation & purification/ Tuberculosis	9002033	19
K15	Tuberculosis arthritis of the knee – an unusual present	04/04/200	India	Case reports / Journal Article	Knee joint/ diagnosis	10707734	3
K16	Acute arthritis and human immunodeficiency virus infection in Rwanda	26/07/1994	Rwanda	Journal Article	Complications/ epidemiology	8014942	32
K17	Arthroplasty in tuberculosis of the knee. Two cases of missed diagnosis.	20/10/1987	England	Case reports / Journal Article	Knee Joint/ Knee prosthesis/ diagnosis	3630669	22
K18	Short-course chemotherapy for tuberculosis in children	07/01/1984	USA	Journal Article/ Research support, Non- U.S. Gov't	Administration & dosage/ drug therapy	6606156	73

Table 6.2: The basic information for the generated ontologies

K No.	Axioms	Logical axioms count	Class count	Individual count	Subclass of axiom count	Functional object property axioms count	Object property domain axiom count	Object property range axiom count	Sub data property of axioms	Class assertion axiom count	Object property assertion axiom count	Data property assertion axiom count	Annotation Assertion count
K1	1338	284	161	19	216	3	4	13	1	19	24	4	844
K2	1363	294	170	21	228	3	4	9	1	22	23	4	848
K3	750	167	88	14	116	3	4	9	1	14	16	4	451
K4	1590	355	193	30	263	3	4	10	1	32	38	4	982
K5	722	156	84	16	104	3	4	5	1	16	19	4	436
K6	1415	323	175	27	241	3	4	11	1	31	28	4	860
K7	974	216	121	22	145	3	4	9	1	24	26	4	585
K8	1295	286	156	23	215	3	4	13	1	24	22	4	800
K9	1110	239	136	18	184	3	4	7	1	19	17	4	687
K10	336	71	36	2	52	3	4	4	1	2	1	4	197
K11	702	164	80	19	97	3	4	5	1	21	29	4	409
K12	457	106	51	12	64	3	4	5	1	14	11	4	258
K13	519	114	61	3	88	3	4	7	1	5	2	4	311
K14	1124	226	139	17	171	3	4	7	1	18	18	4	712
K15	800	167	95	13	119	3	4	10	1	13	13	4	495
K16	796	180	94	19	118	3	4	5	1	20	25	4	473
K17	1172	247	144	15	193	3	4	9	1	17	16	4	736
K18	1276	277	153	22	208	3	4	10	1	24	23	4	794

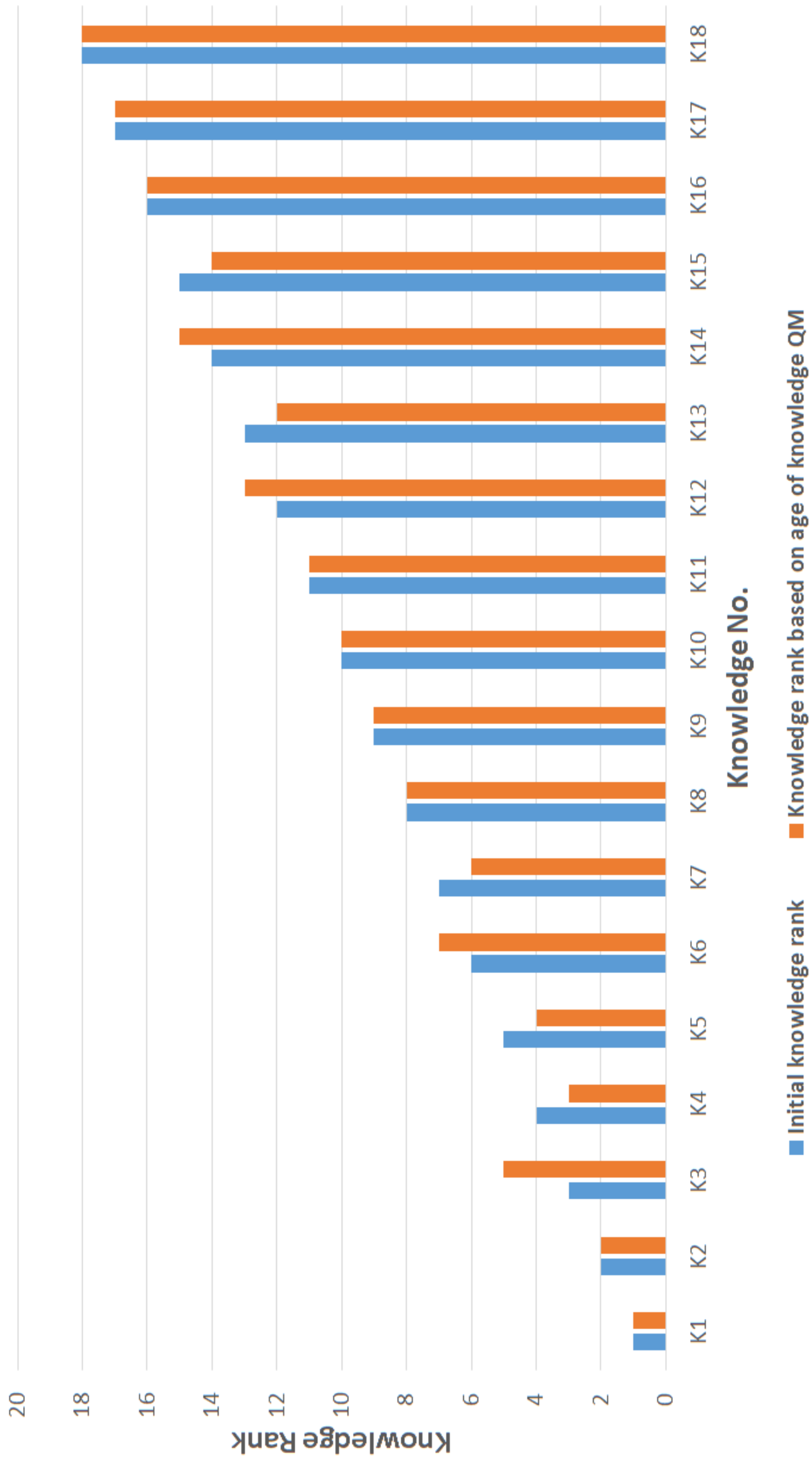


Figure 6.2: Knowledge rank based on the age of knowledge QM compared with the initial knowledge rank

Table 6.3: Knowledge ranking by Age knowledge QM

Knowledge No.	**Initial knowledge rank**	**Date created**	$Age\ (year)$	$Age\ (year/month)$	**Knowledge rank by the age knowledge QM**	d	d^2
K1	1	20/10/2014	3	2/5	1	0	0
K2	2	10/02/2014	3	3/1	2	0	0
K3	3	14/11/2011	6	5/4	5	-2	4
K4	4	29/08/2012	5	4/7	3	1	1
K5	5	14/12/2011	6	5/3	4	1	1
K6	6	02/06/2010	7	6/9	7	1	1
K7	7	07/02/2011	6	6/1	6	1	1
K8	8	29/12/2009	8	7/3	8	0	0
K9	9	27/06/2008	9	8/9	9	0	0
K10	10	08/03/2007	10	10/0	10	0	0
K11	11	13/10/2006	11	10/5	11	0	0
K12	12	15/08/2003	14	13/7	13	1	1
K13	13	24/03/2005	12	12/0	12	1	1
K14	14	26/03/1997	20	20/0	15	1	1
K15	15	04/04/2000	17	16/11	14	1	1
K16	16	26/07/1994	23	22/8	16	0	0
K17	17	20/10/1987	30	29/5	17	0	0
K18	18	07/01/1984	33	33/2	18	0	0

6.3.2 Citation

As mentioned in Chapter 4, the Google scholar APIs have been used to extract the number of citations for each particular knowledge item. In this case, those knowledge items which have been cited more than others usually have a higher place in the ranking list. Table 6.4 indicates the number of citations for each knowledge item. In this table, the column "Initial knowledge rank" shows the rank as retrieved from the PubMed search engine. There is another column that indicates the knowledge rank reached using the citation knowledge QM. Figure 6.3 shows the knowledge ranks in the KQA and PubMed search engine.

As seen in the figure, those older knowledge items have received more citations compare with more recent knowledge. The result is different to the PubMed search engine best match result. It is calculated using Spearman's Rank Correlation between two knowledge rank columns in Table 6.4 where $p \cong -0.65$. In this case, the older knowledge with more citations is at the top of the ranking list. The number of citations for new knowledge is usually less than for older knowledge, especially when the older knowledge is known as reference knowledge item. It is important to consider the fact that the citations might not be real. For example, an article might be cited by its authors in another paper without having any connection between the research topics. Therefore, the quality of knowledge cannot only be guaranteed by citation knowledge QM alone. The new knowledge with few citations might contain useful information that can enrich the health expert's knowledge. More recent knowledge might not be retrieved easily if only the citation knowledge QM is the only means of knowledge ranking.

Table 6.4: Knowledge ranking by citation knowledge QM

Knowledge No.	**Initial knowledge rank**	$Citation No.$	**Knowledge rank by Citation knowledge QM**	d	d^2
K1	1	1	18	-17	289
K2	2	2	17	-15	225
K3	3	11	11	-8	64
K4	4	7	13	-9	81
K5	5	7	14	-9	81
K6	6	9	12	-6	36
K7	7	3	15	-8	64
K8	8	23	5	3	9
K9	9	24	4	5	25
K10	10	23	6	4	16
K11	11	29	3	8	64
K12	12	12	10	2	4
K13	13	18	9	4	16
K14	14	19	8	6	36
K15	15	3	16	-1	1
K16	16	32	2	14	196
K17	17	22	7	10	100
K18	18	73	1	17	289

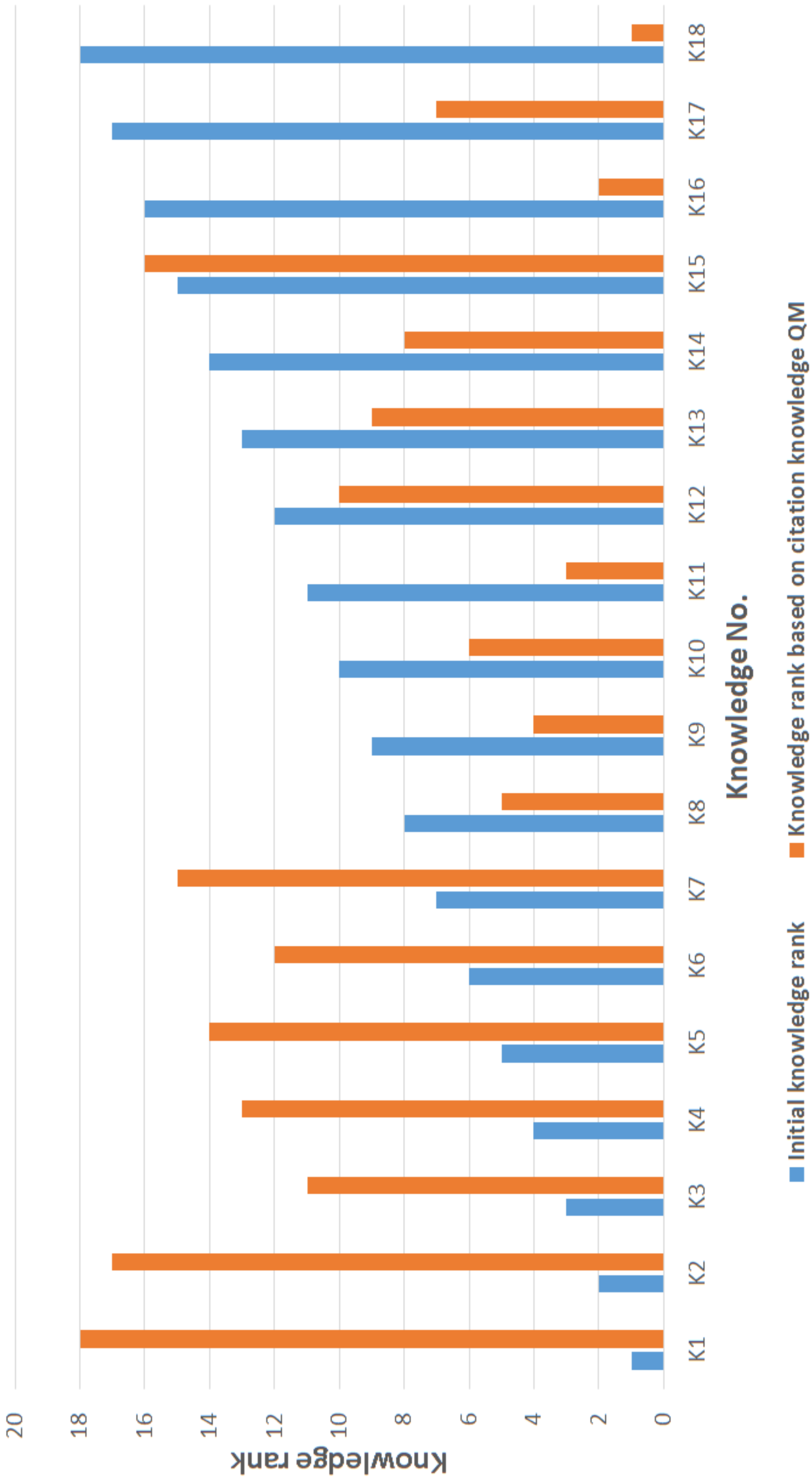


Figure 6.3: Knowledge rank based on the citation knowledge QM compared with the initial knowledge rank

6.3.3 Structure

Calculating the structure of an ontology has been explained in Chapter 5 (Section 5.4.3). As mentioned earlier, Relationship Maturity (RM), Class Maturity (CM), Attribute Maturity (AM), and Inheritance Maturity (AM) have been used to measure the value of an ontological structure. The details of each factor have been explained below.

Relationship Maturity (RM)

The value of RM id divided into the value of RM at the Schema level (RM_S) and the value of RM at the individual level (RM_I).

As mentioned in Chapter 5, to calculate the value of RM_S, the number of relationships ($|R|$) along with the total number of subclasses in the ontology ($|Sub|$) are obtained. The number of relationships can be calculated by the total number of relations between classes at the schema level ($|R^C|$) and individuals at the instance level ($|R^I|$). The ontology information is shown in Table 6.2. As can be seen, the value of *"Subclass of axiom count"* can be utilized as the number of subclasses in the ontology. The *"Object property assertion axiom count"* and *"Object property range axiom count"* can also be used as the number of individual relationships and the number of class relationships, respectively. Note that the class relationships are those relationships which are not identified by "Has_subclass" relationships. The RM_I can also be calculated through the number of individual relationships divided by the class relationships. Based on the previous discussion, the *"Object property assertion axiom count"* and *"Object property range axiom count"* have been used as individual relationships and class relationships respectively. Table 6.5 illustrates the RM score applied to each knowledge item.

Table 6.5: Calculating RM for the knowledge items

Knowledge No.	$\|Sub\|$	$\|R^I\|$	$\|R^C\|$	$\|R\|$	RM_S	RM_I	RM
K1	209	24	13	37	0.1504	1.8462	0.9983
K2	219	23	9	32	0.1275	2.5556	1.3415
K3	111	16	9	25	0.1838	1.7778	0.9808
K4	252	38	10	48	0.1600	3.8000	1.9800
K5	98	19	5	24	0.1967	3.8000	1.9984
K6	233	28	11	39	0.1434	2.5455	1.3444
K7	134	26	9	35	0.2071	2.8889	1.5480
K8	206	22	13	35	0.1452	1.6923	0.9188
K9	177	17	7	24	0.1194	2.4286	1.2740
K10	50	1	4	5	0.0909	0.2500	0.1705
K11	90	29	5	34	0.2742	5.8000	3.0371
K12	58	11	5	16	0.2162	2.2000	1.2081
K13	85	2	7	9	0.0957	0.2857	0.1907
K14	163	18	7	25	0.1330	2.5714	1.3522
K15	113	13	10	23	0.1691	1.3000	0.7346
K16	112	25	9	34	0.2113	5.0000	2.6056
K17	185	16	9	25	0.1190	1.7778	0.9484
K18	201	23	10	33	0.1410	2.3000	1.2205

Class Maturity (CM)

The CM can be computed by dividing the number of those classes that have individuals (C^I) on the total number of classes (C) in the ontology. Note that the C^I refers to the LLC in the ontology. In this regard, the *"Class count"* and *"Class assertion count"* refer to C and C^I which can be used for calculating the CM. Table 6.6 shows the results obtained by CM. In this table, the last column is the CM score for each knowledge item.

Table 6.6: Calculating CM for the knowledge items

Knowledge No.	C^I	C	CM
K1	19	161	0.1180
K2	22	170	0.1294
K3	14	88	0.1591
K4	32	193	0.1658
K5	16	156	0.1026
K6	31	175	0.1771
K7	24	121	0.1983
K8	24	156	0.1538
K9	19	136	0.1397
K10	2	36	0.0556
K11	21	80	0.2625
K12	14	51	0.2745
K13	5	61	0.0820
K14	18	139	0.1295
K15	13	95	0.1368
K16	20	94	0.2128
K17	17	144	0.1181
K18	24	153	0.1569

Attribute Maturity (AM)

AM can be computed by dividing the number of meta-dada ($|annotation|$) used in the classes on the total number of classes (C) in the ontology. AM expresses how attributes and information have been propagated among classes of the ontology. $|annotation|$ can be obtained by *"Annotation assertion axiom count"* and C by the *"Class Count"*. The results achieved by AM are shown in Table 6.7.

Table 6.7: Calculating AM for the knowledge items

Knowledge No.	$\lvert annotation \rvert$	C	AM
K1	844	161	5.2422
K2	848	170	4.9882
K3	451	88	5.1250
K4	982	193	5.0881
K5	436	156	5.1905
K6	860	175	4.9143
K7	585	121	4.8347
K8	800	156	5.1282
K9	687	136	5.0515
K10	197	36	5.4722
K11	409	80	5.1125
K12	258	51	5.0588
K13	311	61	5.0984
K14	712	139	5.1223
K15	495	95	5.2105
K16	473	94	5.0319
K17	736	144	5.1111
K18	794	153	5.1895

Inheritance Maturity (IM)

IM evaluates the hierarchical structures (subclass and superclass relations) in the ontology. The value of IM can be computed by dividing the total number of subclasses of each class in the ontology ($\sum_{c_n \in C} \lvert Sub(c_n, CH) \rvert$). The *"Subclass of axiom count"* shows the total number of subclasses in the ontology. Table 6.8 lists the results of applying IM to the knowledge items.

Table 6.8: Calculating IM for the knowledge items

Knowledge No.	$\sum_{c_n \in C} \lvert Sub(c_n, CH) \rvert$	C	IM
K1	216	161	1.3416
K2	228	170	1.3412
K3	116	88	1.3182
K4	263	193	1.3627
K5	104	156	1.2381
K6	241	175	1.3771
K7	145	121	1.1983
K8	215	156	1.3782
K9	184	136	1.3529
K10	52	36	1.4444
K11	97	80	1.2125
K12	64	51	1.2549
K13	88	61	1.4426
K14	171	139	1.2302
K15	119	95	1.2526
K16	118	94	1.2553
K17	193	144	1.3403
K18	208	153	1.3595

The average of the RM, CM, AM, and IM have been used to calculate the value of the ontological structure. The structure value for each knowledge item is presented in Table 6.9 in the "Structure score" column. In this table, there is a column to show the initial knowledge rank retrieved from the PubMed search engine along with a column to show the knowledge rank after applying the structure knowledge QM. Figure 6.4 represents knowledge ranked by the structure knowledge QM along with the initial knowledge rank. The differences shown in Figure 6.4 demonstrate that the process of knowledge quality assessment in the PubMed search engine does not usually consider the structure of the knowledge. The value of Spearman's Rank Correlation between two knowledge rank columns in Table 6.9 ($p \cong 0.025$) indicates that there is no perfect match between initial knowledge rank and new rank of knowledge by structure. Considering the structure of the knowledge could be useful in showing the maturity of the knowledge.

Table 6.9: Knowledge ranking by structure knowledge QM

Knowledge No.	**Initial knowledge rank**	RM	CM	AM	IM	**Structure score**	**Knowledge rank by structure knowledge QM**	d	d^2
K1	1	0.9983	0.1180	5.2422	1.3416	1.9250	12	-11	121
K2	2	1.3415	0.1294	4.9882	1.3412	1.9501	9	-7	49
K3	3	0.9808	0.1591	5.1250	1.3182	1.8958	13	-10	100
K4	4	1.9800	0.1658	5.0881	1.3627	2.1492	3	1	1
K5	5	1.9984	0.1026	5.1905	1.2381	2.1324	4	1	1
K6	6	1.3444	0.1771	4.9143	1.3771	1.9532	8	-2	4
K7	7	1.5480	0.1983	4.8347	1.1983	1.9448	11	-4	16
K8	8	0.9188	0.1538	5.1282	1.3782	1.8948	14	-6	36
K9	9	1.2740	0.1397	5.0515	1.3529	1.9545	7	2	4
K10	10	0.1705	0.0556	5.4722	1.4444	1.7857	17	-7	49
K11	11	3.0371	0.2625	5.1125	1.2125	2.4062	1	10	100
K12	12	1.2081	0.2745	5.0588	1.2549	1.9491	10	2	4
K13	13	0.1907	0.0820	5.0984	1.4426	1.7034	18	-5	25
K14	14	1.3522	0.1295	5.1223	1.2302	1.9586	6	-8	64
K15	15	0.7346	0.1368	5.2105	1.2526	1.8336	16	-1	1
K16	16	2.6056	0.2128	5.0319	1.2553	2.2764	2	14	196
K17	17	0.9484	0.1181	5.1111	1.3403	1.8795	15	2	4
K18	18	1.2205	0.1569	5.1895	1.3595	1.9816	5	13	169

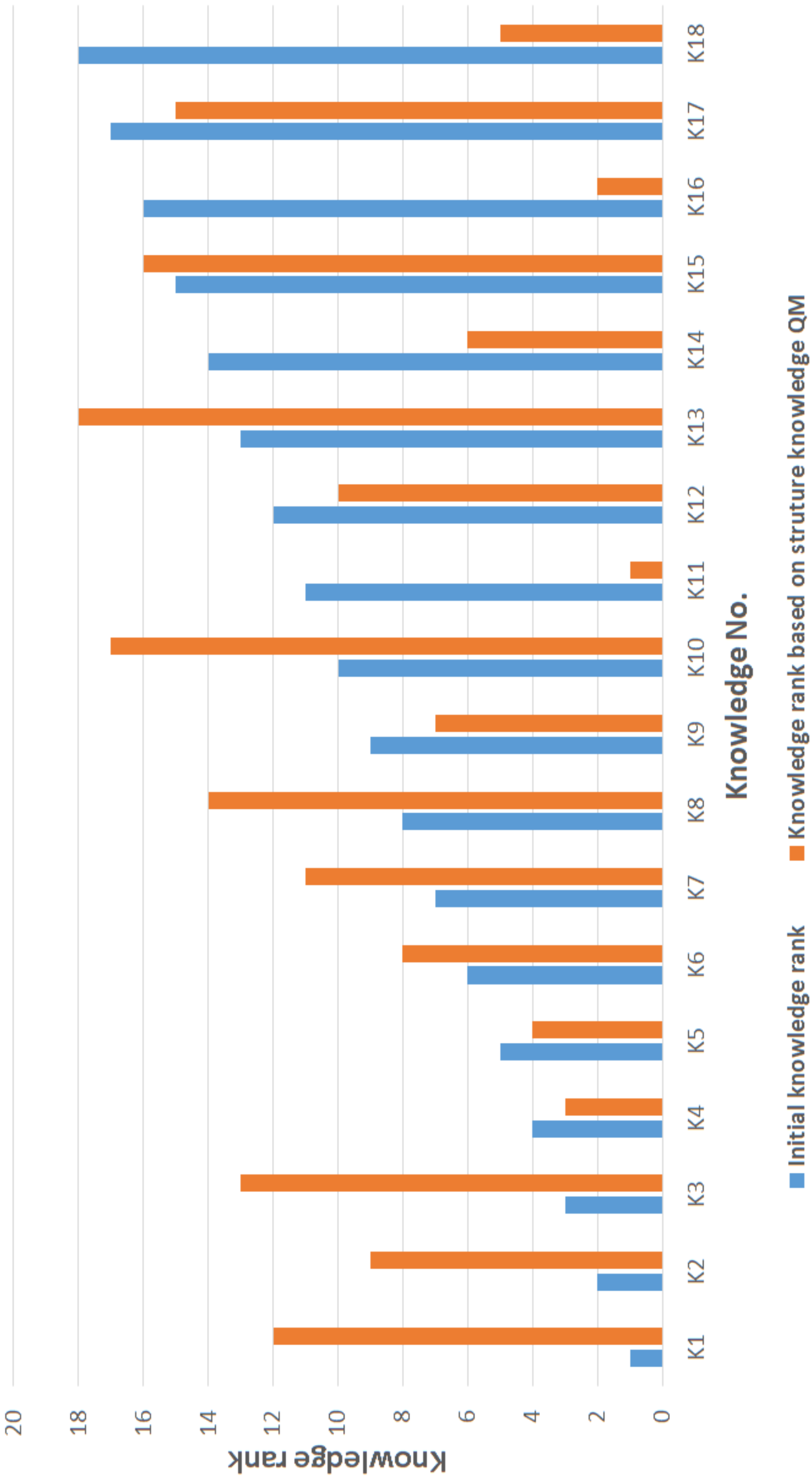


Figure 6.4: Knowledge rank based on the structure knowledge QM compared with the initial knowledge rank

6.3.4 Relevancy

This knowledge QM indicates how relevant knowledge is to a given query. In this research, a well-known text mining technique called TF-IDF, which was discussed in Chapter 5 has been used. The value of relevancy depends on two main factors. The first factor is knowledge weight (KW) that evaluates the value of the TF-IDF without considering the given query. The second factor is the knowledge relevancy score (KRS) that assesses the value of TF-IDF through consideration of the given query for each particular knowledge item. The relationship between these two factors helps to rank knowledge based on the relevancy knowledge QM. During the first stage, the knowledge item is ranked by KRS which considers common terms between the query and the knowledge item. There might be the same KRS scores for some knowledge items if they have an equal number of common terms in their body. For example, if two knowledge item have two "Tuberculosis Arthritis" terms, the KRS score is the same for both knowledge items. In this case, the KW score helps to rank the knowledge items. This factor shows how much information a knowledge item has.

Table 6.10 presents the results achieved by the applying the relevancy knowledge QM. In this table, the "Initial knowledge rank" column shows knowledge ranking retrieved from the PubMed search engine. There is another column that indicates the knowledge ranking applied by the relevancy knowledge QM. The table also shows the KW and KRS scores of knowledge items in separate columns. Figure 6.5 illustrates the knowledge ranking by applying relevancy knowledge QM to compare it with the initial knowledge ranking.

Table 6.10: Knowledge ranking by relevancy knowledge QM

Knowledge No.	**Initial knowledge rank**	KW	KRS	**Knowledge rank by Relevancy knowledge QM**	d	d^2
K1	1	56.54	0.17	12	-11	121
K2	2	42.68	0.19	11	-9	81
K3	3	104.24	0.05	15	-8	64
K4	4	57.70	0.22	4	0	0
K5	5	50.46	0.24	1	4	16
K6	6	102.03	0.20	7	-1	1
K7	7	154.35	0.22	3	4	16
K8	8	186.58	0.20	6	2	4
K9	9	66.78	0.19	10	-1	1
K10	10	0.0	0.0	18	-8	64
K11	11	64.95	0.23	2	9	81
K12	12	71.36	0.05	16	-4	16
K13	13	41.52	0.22	5	8	64
K14	14	32.56	0.05	17	-3	9
K15	15	16.29	0.16	13	2	4
K16	16	97.25	0.19	9	7	49
K17	17	10.36	0.16	14	3	9
K18	18	115.61	0.19	8	10	100

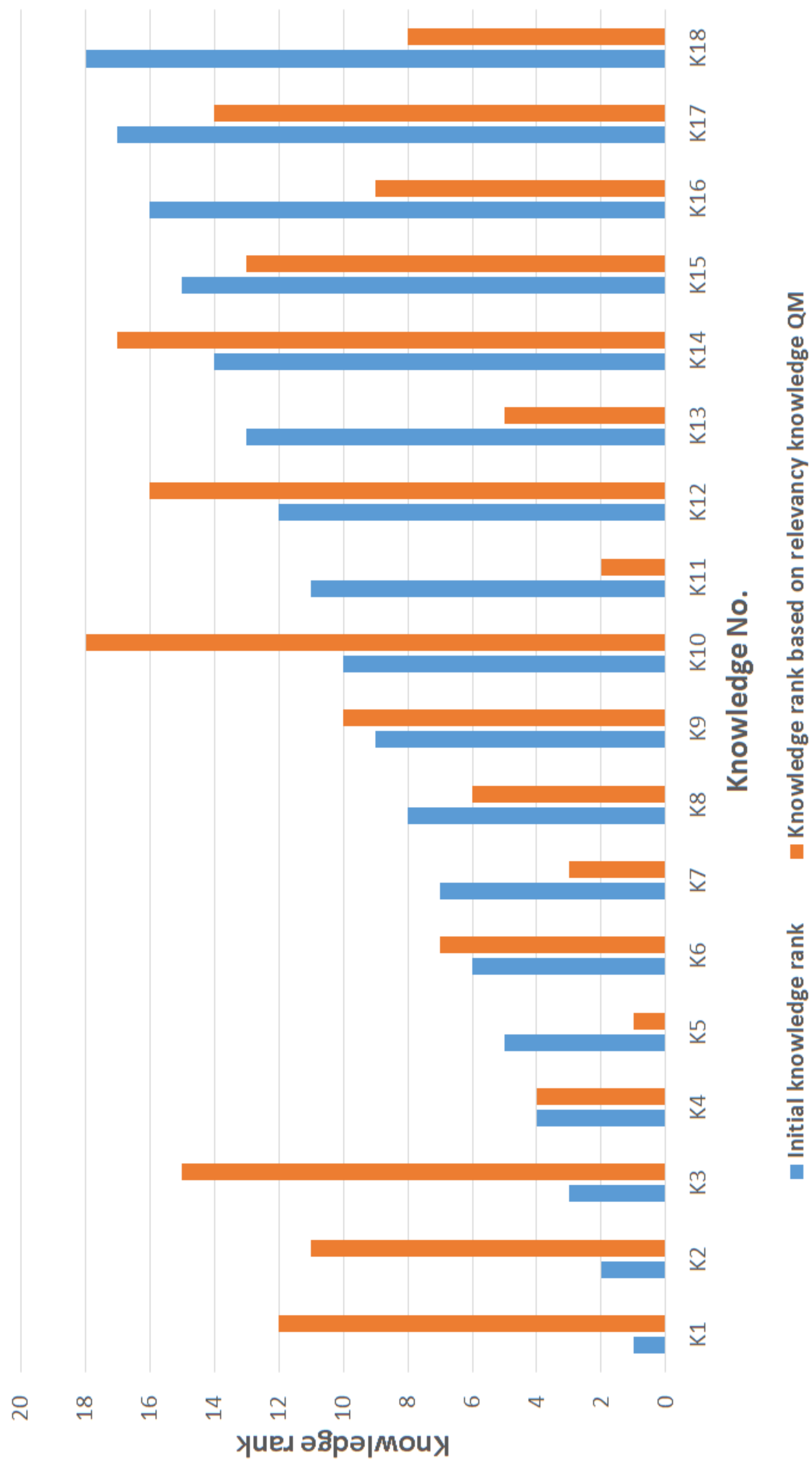


Figure 6.5: Knowledge rank based on relevancy knowledge QM compared with initial knowledge rank

As seen in Figure 6.5, knowledge ranked by applying the relevancy knowledge QM differs from the initial knowledge rank retrieved from the PubMed search engine. The lack of similarity between "Knowledge rank based on relevancy knowledge QM" (orange line) with "Initial knowledge rank" (blue line) shows that the PubMed search engine (with the best match option) does not completely check the relevance of extracted knowledge. In this search engine the relevancy has been utilized to extract related knowledge, however, the knowledge will not be completely ranked from the most relevant knowledge to the least relevant one. To validate this claim, Spearman's Rank correlation has been applied to the rank columns in Table 6.10. The value of this correlation is around 0.28 which indicates there is no perfect similarity and link between initial rank and knowledge rank by relevancy.

As discussed before, the KQA uses the abstract of the knowledge item and MeshHeading concepts in the knowledge item to assess the quality of knowledge. Therefore, the knowledge, without abstract or MeshHeadings, receives a low relevancy score. Thereby, the knowledge item got a lower rank in the set of extracted knowledge items.

The lack of checking the relevancy of knowledge can also be highlighted in K10 which contains no abstract or too short information in MeshHeading concepts. K10 without having a related abstract or MeshHeading terms gets a better place compared with other knowledge in the PubMed search engine which contain more information. However, it would be in a lower ranked place based on the KQA approach. It is vital to check the relevancy of extracted knowledge in the decision making process.

6.3.5 Accuracy

One of the main knowledge QMs in the KQA is accuracy. In order to compute the accuracy value for each knowledge item, the KQA takes advantage of ontology matching and NLP techniques. Comparing ontologies helps to find knowledge with more concepts and relationships along with more meaning to use in the KQA. The process of evaluating with the accuracy knowledge QM depends on two main factors: Lexical Similarity (LS) and Semantic Similarity (SS). SS refers to the concept of ontology matching while the LS refers to NLP techniques. In the following, the results of each factor are discussed in detail. As discussed in Chapter 5, to compare ontologies, the KQA firstly checks available knowledge in the central knowledge repository. If the knowledge is related to the query, it will be considered as the main knowledge item. Otherwise, the KQA considers the first knowledge item retrieved from PubMed the main knowledge item. The system then compares other ontologies with the main one. Except for the main ontology that is always placed at the top, the others are ranked based on LS and SS values.

Lexical Similarity (LS)

This factor has been used to assess the similarity of terms among different ontologies. To compute the similarity of terms among ontologies, the ED algorithm has been applied (See Algorithm 2). LS can be computed through Equation (5.18) (see Chapter 5, Section 5.4.4, Accuracy subsection) for each part of the ontology. Finally, the average of LSs indicates the value of LS for a particular ontology.

Semantic Similarity (SS)

The SS assesses the relationships among ontological classes and the related individuals at the leaf-level. The value of SS depends on two main criteria, class hierarchy similarity (CHS) and relationship similarity (RS).

In order to calculate the value of CHS, there is a need to compute the CHS for any individual belonging to the LLC (CHS_{c_n}). The averaged $CHS(\overline{CHS})$ shows the similarity value of the class hierarchy. This factor applies to those groups of classes which contain some individuals. The RS calculates the ranges and domains of relations where individuals belong to the LLC. The averaged $RS(\overline{RS})$ indicates the similarity value of relationships. The average of $\overline{CHS}$ and $\overline{RS}$ shows the SS value for each knowledge item. Table 6.11 represents the accuracy score after applying LS and SS for each knowledge item extracted from the PubMed search engine. It also indicates the ranking order for knowledge items after applying the accuracy knowledge QM. The "Initial knowledge rank" column is the knowledge rank retrieved from the PubMed search engine. There is also a column that shows the knowledge rank using the accuracy knowledge QM. The table also contains columns for the LS and SS scores. Moreover, the "Accuracy score" column shows the accuracy score of each knowledge derived from the LS and SS scores. Figure 6.6 illustrates the new ranking of knowledge items based on accuracy to compare it with the initial knowledge ranking. The Spearman's Rank Correlation ($p \cong 0.23$) shows low similarity between new knowledge rank and initial knowledge rank.

As discussed in Sub-subsection 5.4.1, there is no change to the rank of the main knowledge item. It is always in first place of the knowledge ranking in terms of accuracy. In this way, by calculating the KQI, the main knowledge item receives a more accurate knowledge ranking for use in the KQA. The KQI considers all of the knowledge QMs and gives a knowledge rank based on all of them. The results of the KQI calculation are discussed next.

Table 6.11: Knowledge ranking by accuracy knowledge QM

Knowledge No.	**Initial knowledge rank**	LS	CHS	RS	SS	**Accuracy score**	**Knowledge rank by Accuracy knowledge QM**	d	d^2
K1	1	1	1	1	1	1.0000	1	0	0
K2	2	0.7822	0.4722	0.104	0.2881	0.5352	4	2	4
K3	3	0.5111	0.1412	0.0755	0.10835	0.3097	15	-12	144
K4	4	0.8272	0.4398	0.1559	0.29785	0.5625	2	2	4
K5	5	0.5458	0.3333	0.1012	0.21725	0.3815	12	-7	49
K6	6	0.6286	0.4555	0.0331	0.2443	0.4365	10	-4	16
K7	7	0.6017	0.2301	0.0456	0.13785	0.3698	14	-7	49
K8	8	0.765	0.412	0.2668	0.3394	0.5522	3	5	25
K9	9	0.7326	0.3287	0.1814	0.25505	0.4938	6	3	9
K10	10	0.4105	0.1203	0	0.06015	0.2353	18	-8	64
K11	11	0.5642	0.3583	0.0412	0.19975	0.3820	11	0	0
K12	12	0.4691	0.187	0.0726	0.1298	0.2995	16	-4	16
K13	13	0.4523	0.1203	0	0.06015	0.2562	17	-4	16
K14	14	0.7153	0.2888	0.0476	0.1682	0.4418	9	5	25
K15	15	0.7159	0.3425	0.1253	0.2339	0.4749	8	7	49
K16	16	0.5584	0.3444	0.0478	0.1961	0.3773	13	3	9
K17	17	0.7525	0.3829	0.1316	0.25725	0.5049	5	12	144
K18	18	0.6974	0.3842	0.132	0.2581	0.4778	7	11	121

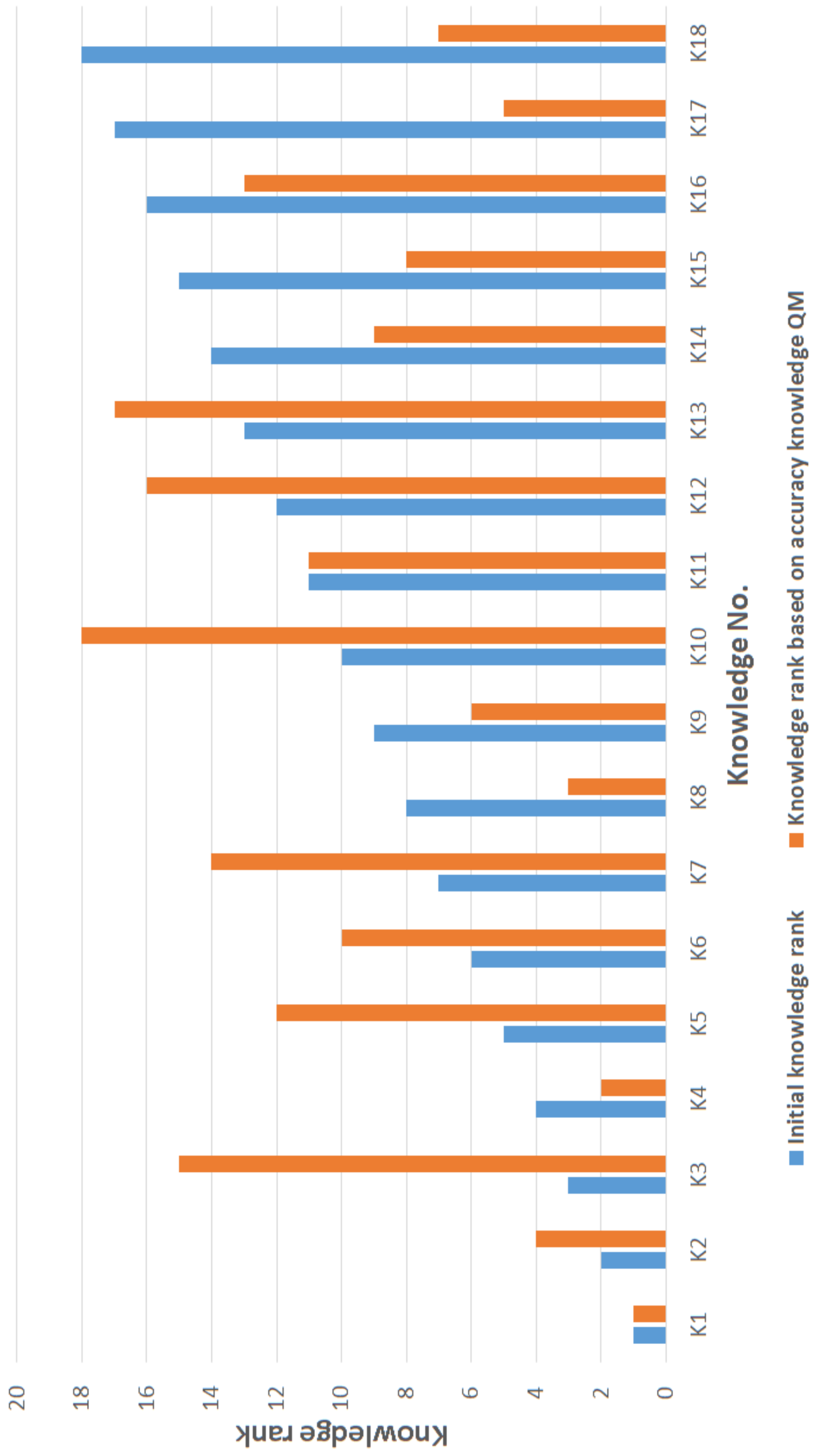


Figure 6.6: Knowledge rank based on the accuracy knowledge QM compared with initial knowledge rank

6.3.6 Calculating and ranking knowledge by KQI

This section focuses on evaluating the KQI to show how much the knowledge item is qualified to compare with a given query. The main goal of this thesis is to show the applicability of the KQA for discovering high quality knowledge. The KQI has been calculated by using knowledge QMs. It is used to assess the quality of a particular knowledge item in two different forms, linear and weighted (refer to the equations (5.27) and (5.28)). The results of applying the KQI are presented in Table 6.12.

All of the knowledge QM scores such as age, citation, structure, relevancy and accuracy have been utilized in the KQI calculation. In table 6.12, there are columns for the initial knowledge rank retrieved from the PubMed search engine and the new ranking of knowledge for KQI_{Linear} and $KQI_{Weighted}$. Figure 6.7 shows the knowledge ranking based on KQI_{linear} and $KQI_{weighted}$ along with the initial ranked knowledge retrieved from the PubMed search engine.

As seen in Figure 6.7, there is not a large difference between the KQI_{linear} and $KQI_{weighted}$ ranking results and they are quite compatible. The Spearman's Rank Correlation values for both KQI ranks to compare with initial rank are same ($p \cong 0.44$). This figure shows that the citation score might effect the results of KQI. In other words, the results achieved by KQI are similar to results of the citation score. This might be due to the citation score's large value compared with the other knowledge QM scores. The other knowledge QM which might effect the KQI result is age. In calculating age of knowledge independently, the knowledge is ranked based on the newest (low age value) to the oldest (high age value) knowledge. But, in KQI calculation, the larger age value gives a higher rank to a knowledge item. Figure 6.8 shows the results of KQI considering only the age and citation knowledge QMs. Comparing Figure 6.7 and Figure 6.8 it is clear that the knowledge rank diagrams are quite similar. So, the KQI might be inspired by age and citation knowledge QMs.

Table 6.12: Knowledge ranking by KQI

K No.	Initial knowledge rank	Age score	Citation score	Structure score	Relevancy score	Accuracy score	KQI_{Linear}	$KQI_{Weighted}$	Knowledge rank by KQI_{Linear}	Knowledge rank by $KQI_{Weighted}$	d_{Linear}	d^2_{Linear}	$d_{Weighted}$	$d^2_{Weighted}$
K1	1	3	1	1.9250	0.17	1.0000	7.095	1.3870	18	18	-17	289	-17	289
K2	2	3	2	1.9501	0.19	0.4528	7.5928	1.4484	17	17	-15	225	-15	225
K3	3	6	11	1.8958	0.05	0.2426	19.1883	3.6176	12	12	-9	81	-9	81
K4	4	5	7	2.1492	0.22	0.4743	14.8434	2.8141	15	15	-11	121	-11	121
K5	5	6	7	2.1324	0.24	0.3268	15.6991	2.9753	14	14	-9	81	-9	81
K6	6	7	9	1.9532	0.20	0.3724	18.5255	3.5140	13	13	-7	49	-7	49
K7	7	6	3	1.9448	0.22	0.2925	11.4573	2.1879	16	16	-9	81	-9	81
K8	8	8	23	1.8948	0.20	0.4813	33.576	6.3239	8	8	0	0	0	0
K9	9	9	29	1.9545	0.19	0.4142	35.5586	6.6976	6	6	3	9	3	9
K10	10	10	24	1.7857	0.0	0.1769	34.9625	6.5826	7	7	3	9	3	9
K11	11	11	23	2.4062	0.23	0.3212	42.9573	8.0818	4	4	7	49	7	49
K12	12	14	29	1.9491	0.05	0.2429	28.2419	5.3795	10	10	2	4	2	4
K13	13	12	12	1.7034	0.22	0.1909	32.1142	6.0797	9	9	4	16	4	16
K14	14	20	18	1.9586	0.05	0.3506	41.3658	7.8827	5	5	9	81	9	81
K15	15	17	19	1.8336	0.16	0.3946	22.3882	4.3357	11	11	4	16	4	16
K16	16	23	3	2.2764	0.19	0.3169	57.7832	10.9572	2	2	14	196	14	196
K17	17	30	22	1.8795	0.16	0.4223	54.4617	10.4226	3	3	14	196	14	196
K18	18	33	73	1.9816	0.19	0.4045	108.5025	20.4809	1	1	17	289	17	289

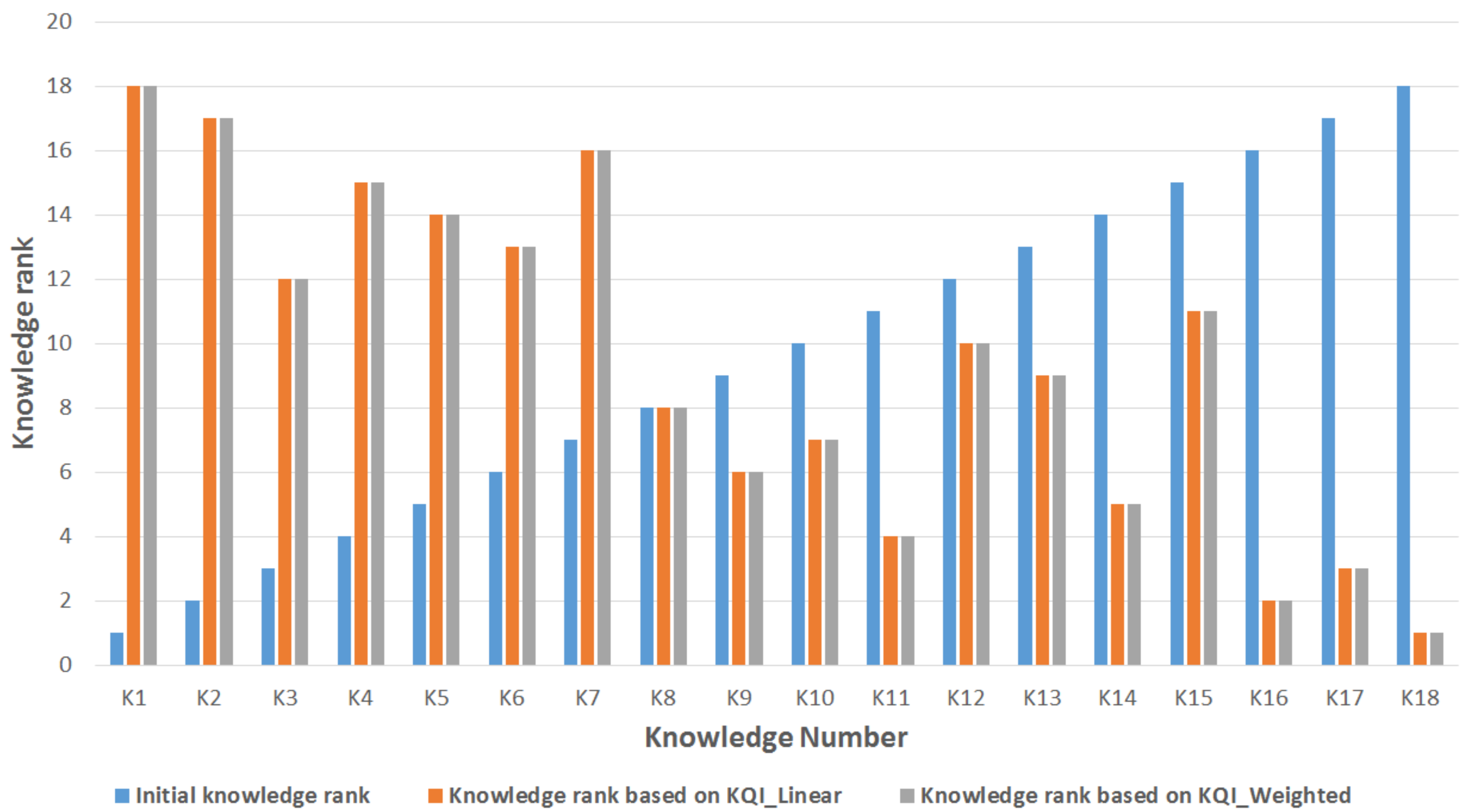


Figure 6.7: Knowledge rank based on KQI compared with initial knowledge rank (using all knowledge QMs: age, citation, structure, relevancy, and accuracy)

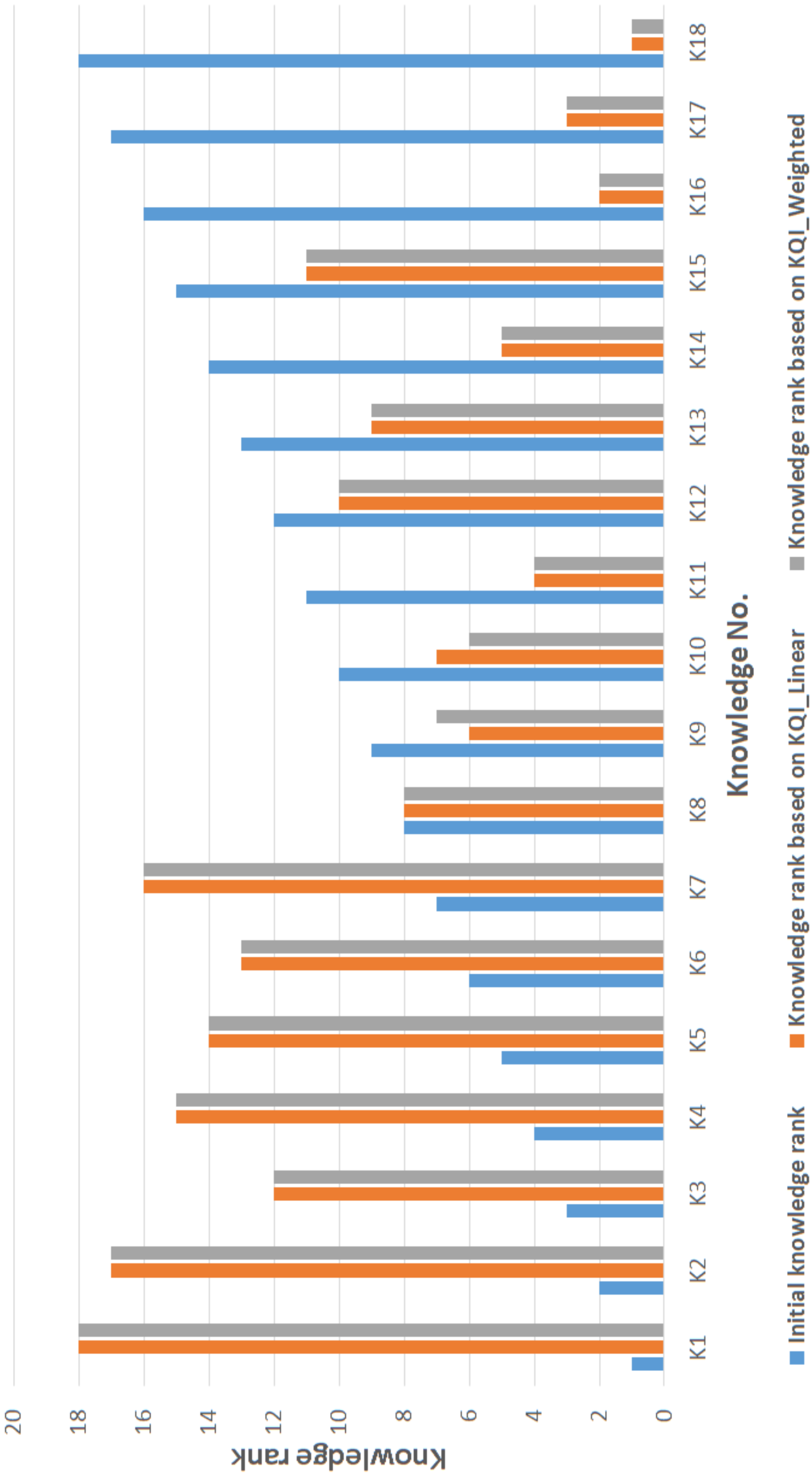


Figure 6.8: Knowledge rank based on KQI compared with initial knowledge rank (using age and citation knowledge QMs)

Different combinations of knowledge QMs for calculating KQI have been utilized in this research. The aim is to find the most accurate KQI score to rank knowledge. Firstly, the KQI was calculated by structure, relevancy and accuracy (See Figure 6.9). The comparison between diagrams of Figure 6.9 and Figure 6.8 shows significant changes in the knowledge ranking by KQI. It may prove that the KQI might be affected by the age and citation knowledge QMs. The results of the knowledge rank in Figure 6.9 indicates that the KQI might be affected most by the accuracy score when the age and citation scores have not been used.

The next combinations used to calculate the KQI was a combination for intrinsic knowledge QMs (Age, Citation and Structure) and a combination for contextual knowledge QMs (Relevancy and Accuracy). Figure 6.10 and Figure 6.11 show knowledge ranking achieved by KQI based on intrinsic knowledge QMs and contextual knowledge QMs respectively to compare them with the initial knowledge ranking. To evaluate the performance of the KQI and the knowledge QMs, a questionnaire was conducted to ask health experts their opinions. The results of the questionnaire are discussed in Phase 3 to show how valid the KQI and knowledge QMs are.

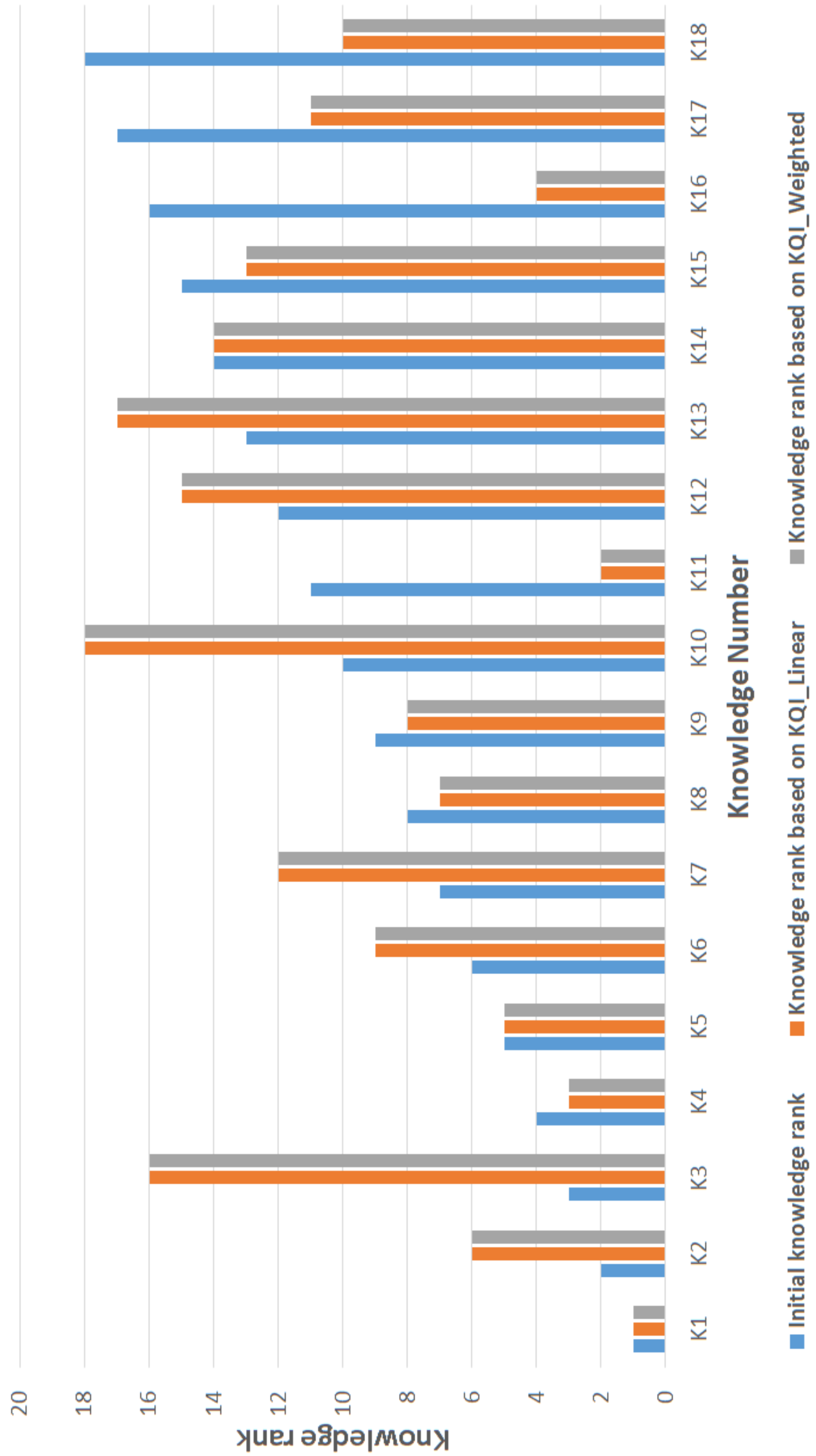


Figure 6.9: Knowledge rank based on KQI compared with initial knowledge rank (using structure, relevancy, and accuracy knowledge QMs)

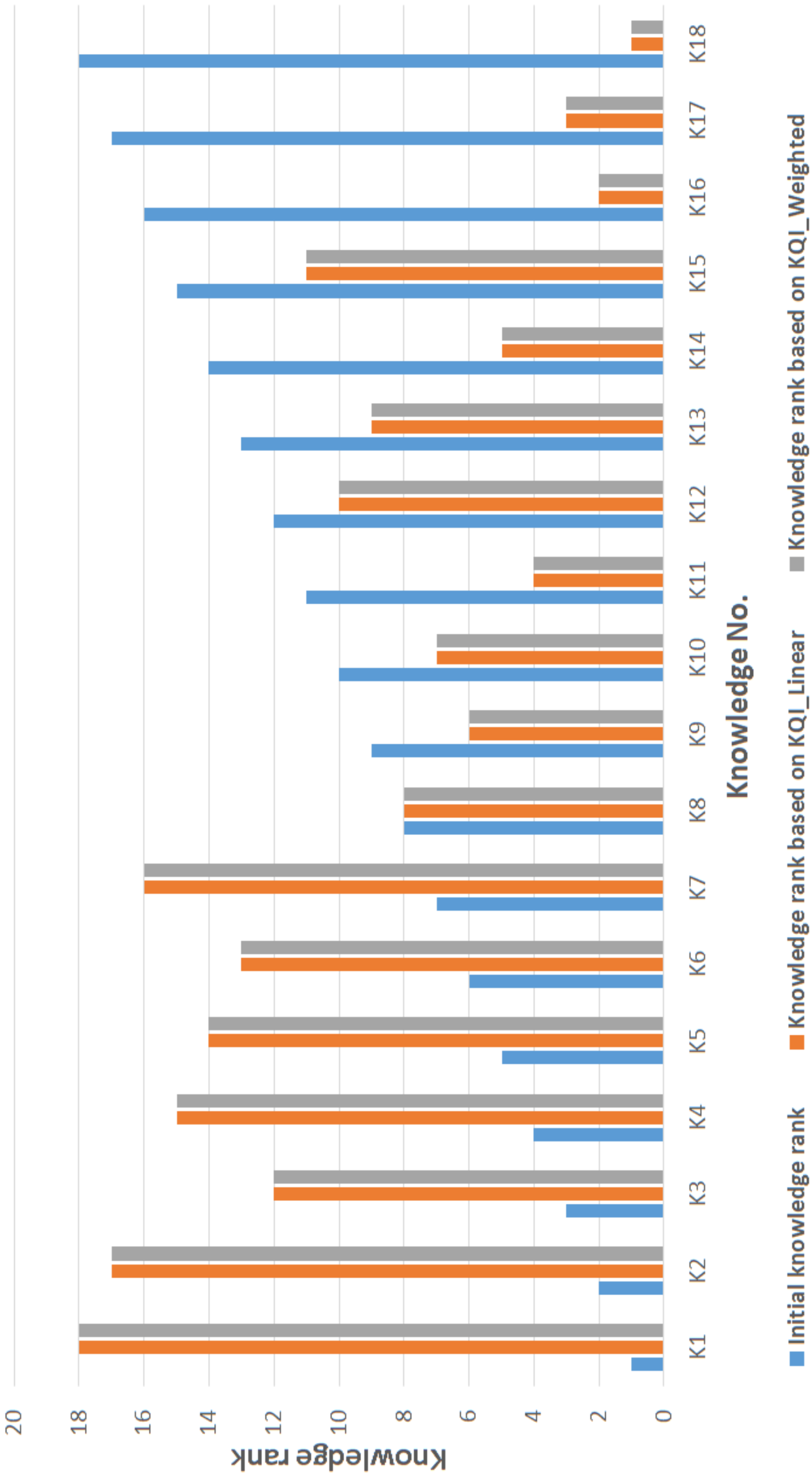


Figure 6.10: Knowledge rank based on KQI compared with initial knowledge rank (using age,citation, and structure knowledge QMs)

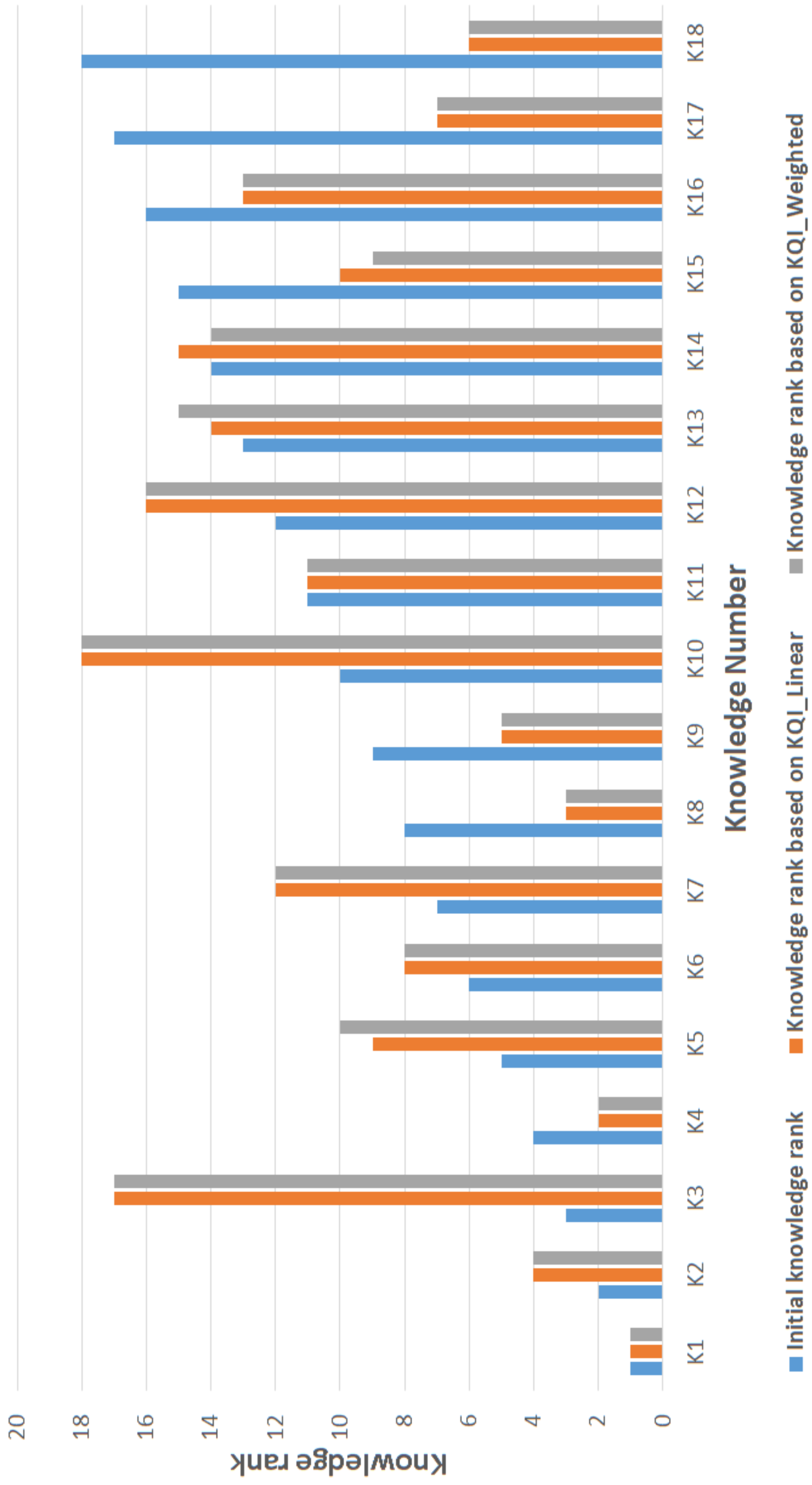


Figure 6.11: Knowledge rank based on KQI compared with initial knowledge rank (using relevancy and accuracy knowledge QMs)

6.4 Phase 3

This phase compares the results obtained and ranked by the KQA with the health experts' opinions. This comparison has been conducted by considering the results achieved by the knowledge QMs. In this regard, an anonymous questionnaire was distributed among health experts to receive their opinions. Note that the method and structure of this questionnaire is quite similar to the questionnaire mentioned in Section 3.3.2. The questions used in this questionnaire are about evaluating the quality of a given knowledge item by the health experts (See Appendix D). The knowledge items used in the questionnaire are those were assessed in the KQA. More precisely, they are based on the initial knowledge ranking retrieved from the search engine.

Similar to the previous questionnaire, 10 health experts participated in this questionnaire. It is necessary to note that in this questionnaire, the title and abstract of the knowledge items were given to the health experts. The definitions of the knowledge QMs have been also provided for them to clarify the purpose of each QM in the research. In this questionnaire, health experts confirm the quality of knowledge after reviewing the titles and abstracts. In the questionnaire, the health experts ranked the knowledge based on age and citation knowledge QMs. The results were the same as KQA results. By considering these knowledge QMs, the knowledge will be ranked and stored based on age and citations. Therefore, the results between health experts and KQA approach are the same. The structure knowledge QM is not considered at this phase as it is only related to the ontological structure of the knowledge. The results of the questionnaire for relevancy and accuracy are discussed next. Table 6.13 shows the results of the questionnaire as evaluated by the health experts.

Table 6.13: The results of the questionnaire to verify the relevancy and accuracy of extracted knowledge

Knowledge No.	**Knowledge QM**	**Participants**										**Total**	**Total**
		A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**No. of YES**	**No. of NO**
K1	Relevant?	Y	N	Y	Y	Y	N	Y	Y	N	Y	7	3
	Accurate?	Y	N	Y	Y	Y	N	Y	Y	N	Y	7	3
K2	Relevant?	Y	Y	N	Y	Y	N	Y	N	N	Y	6	4
	Accurate?	Y	Y	N	Y	Y	N	Y	N	N	Y	6	4
K3	Relevant?	Y	Y	N	Y	N	N	Y	N	Y	N	5	5
	Accurate?	N	Y	N	Y	N	N	Y	N	Y	N	4	6
K4	Relevant?	Y	Y	Y	N	Y	N	Y	Y	Y	N	7	3
	Accurate?	Y	Y	Y	N	Y	N	Y	Y	Y	N	7	3
K5	Relevant?	Y	Y	N	Y	Y	Y	N	Y	Y	Y	8	2
	Accurate?	N	N	N	N	N	N	N	Y	N	Y	2	8
K6	Relevant?	Y	N	N	Y	Y	N	Y	Y	Y	Y	7	3
	Accurate?	Y	N	N	N	N	N	Y	Y	Y	Y	5	5
K7	Relevant?	Y	Y	Y	Y	N	Y	N	Y	Y	Y	8	2
	Accurate?	N	N	N	N	N	N	N	Y	N	N	1	9
K8	Relevant?	Y	N	Y	Y	Y	Y	Y	Y	Y	N	8	2
	Accurate?	Y	N	Y	Y	Y	Y	Y	Y	Y	N	8	2
K9	Relevant?	Y	N	N	Y	Y	Y	N	Y	N	Y	6	4
	Accurate?	N	N	N	Y	Y	Y	N	Y	N	Y	5	5
K10	Relevant?	N	N	N	N	N	N	N	Y	N	N	1	9
	Accurate?	N	N	N	N	N	N	N	N	N	N	0	10
K11	Relevant?	N	N	N	N	N	Y	Y	N	Y	Y	4	6
	Accurate?	N	N	N	N	N	Y	Y	N	Y	N	3	7
K12	Relevant?	Y	Y	Y	N	N	Y	N	N	N	Y	5	5
	Accurate?	N	Y	N	N	N	Y	N	N	N	N	2	8
K13	Relevant?	Y	Y	N	N	Y	Y	Y	Y	Y	Y	8	2
	Accurate?	N	N	N	N	N	N	N	Y	N	N	1	9
K14	Relevant?	Y	Y	N	N	N	N	Y	Y	N	Y	5	5
	Accurate?	Y	Y	N	N	N	N	N	Y	N	N	3	7
K15	Relevant?	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	9	1
	Accurate?	Y	N	Y	N	N	N	Y	Y	Y	Y	6	4
K16	Relevant?	N	Y	N	N	N	N	Y	N	N	Y	3	7
	Accurate?	N	N	N	N	N	N	N	N	N	Y	1	9
K17	Relevant?	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	10	0
	Accurate?	N	Y	N	Y	Y	Y	Y	Y	N	Y	7	3
K18	Relevant?	N	N	Y	N	N	N	Y	Y	N	Y	4	6
	Accurate?	N	N	Y	N	N	N	Y	Y	N	Y	4	6

Table 6.14 compares the knowledge rank based on relevancy and accuracy by KQA approach and the health experts' opinions. Note that the total number of Y (i.e., Yes) has been used for ranking the knowledge. The ranking order follows the initial knowledge rank retrieved from the PubMed search engine, when the number of Y was the same for the two knowledge QMs. In this table, there are separate columns for each of the knowledge ranking by relevancy and accuracy from both the KQA approach and health experts.

Figures 6.12 and 6.13 represent the differences between KQA approach results and health experts' results in terms of the relevancy and accuracy knowledge QMs. The similarity between the results has been calculated through the Spearman's Rank Correlation. The results achieved by this correlation ($p_{Relevancy(healthexperts)} \cong 0.18$, $p_{Accuracy(healthexperts)} \cong 0.36$) shows that the relevancy and accuracy of the knowledge ranked by KQA and health experts are close and compatible.

Figure 6.12 compares the relevancy results from the health expert and the KQA knowledge ranking. As seen, the result is compatible in some cases and is completely different in others. One of the reasons for such differences could be related to the dependency of the KQA mechanism on the term frequency method. By considering the frequency term method, the relevancy of knowledge is based on keywords and concepts common to both queries and knowledge. This gap has been solved in assessing accuracy of knowledge in the KQA. As seen in Figure 6.13, the results obtained by the system are similar to those of the health experts. Assessing the accuracy score of knowledge using ontological structures is quite acceptable. In future work, SW technologies will be used more for improving knowledge QM assessments. There also needs to be more investigation about knowledge QM measurements to provide more accurate results.

Table 6.14: Comparing the knowledge ranking between health experts and KQA approach (in terms of relevancy and accuracy)

Knowledge No.	**Knowledge rank based on Relevancy (by health experts)**	**Knowledge rank based on Accuracy (by health experts)**	**Knowledge rank based on relevancy (by KQA approach)**	**Knowledge rank based on accuracy (by KQA approach)**	d **for relevancy (by health experts)**	d^2 **for relevancy (by health experts)**	d **for Accuracy (by health experts**	d^2 **for Accuracy (by health experts**
K1	7	2	12	1	-6	36	-1	1
K2	10	5	11	4	-8	64	-3	9
K3	12	9	15	15	-9	81	-6	36
K4	8	3	4	2	-4	16	1	1
K5	3	13	1	12	2	4	-8	64
K6	9	7	7	10	-3	9	-1	1
K7	4	15	3	14	3	9	-8	64
K8	5	1	6	3	3	9	7	49
K9	11	8	10	6	-2	4	1	1
K10	18	18	18	18	-8	64	-8	64
K11	15	11	2	11	-4	16	0	0
K12	13	14	16	16	-1	1	-2	4
K13	6	16	5	17	7	49	-3	9
K14	14	12	17	9	0	0	2	4
K15	2	6	13	8	13	169	9	81
K16	17	17	9	13	-1	1	-1	1
K17	1	4	14	5	16	256	13	169
K18	16	10	8	7	2	4	8	64

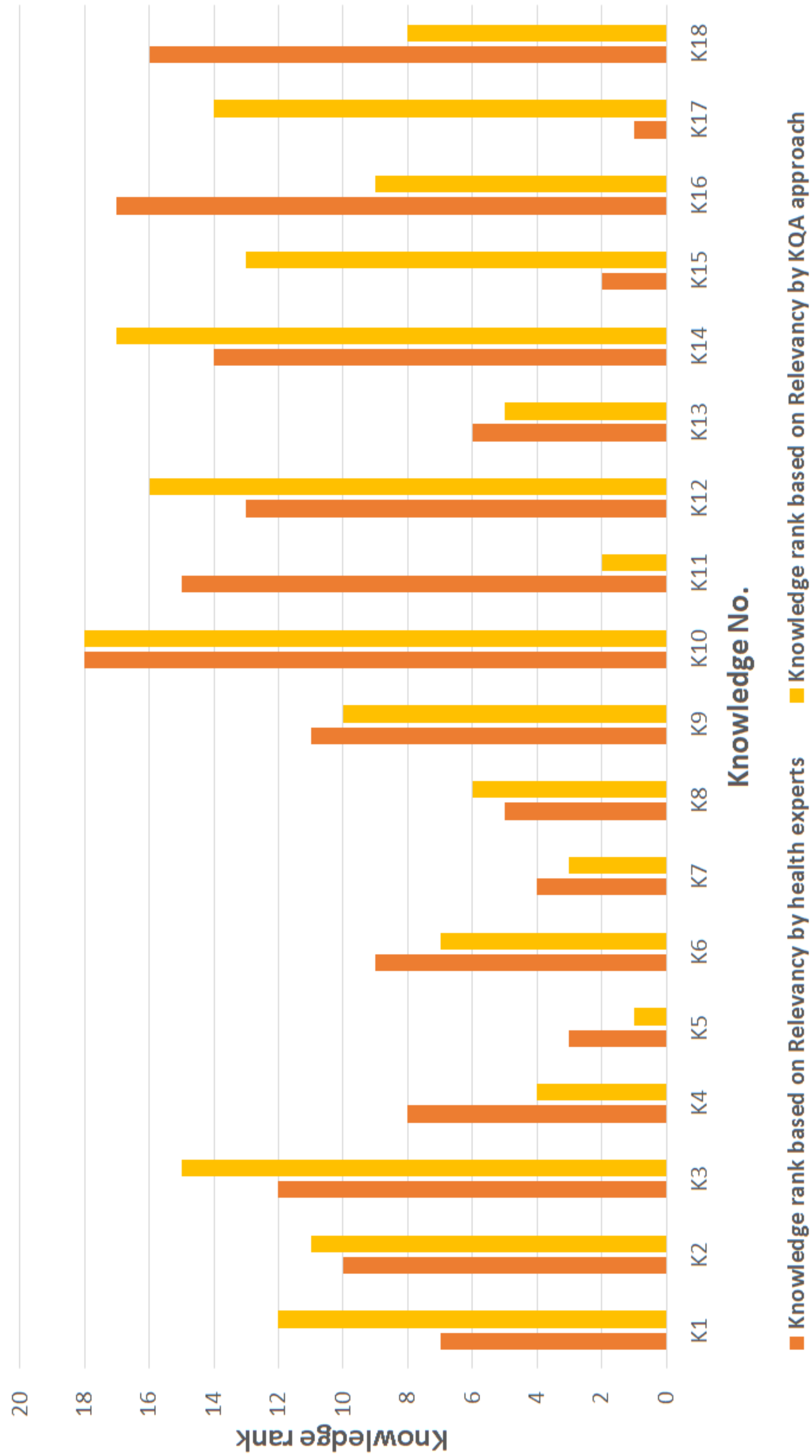


Figure 6.12: Comparing knowledge rank based on relevancy between the KQA approach and health experts

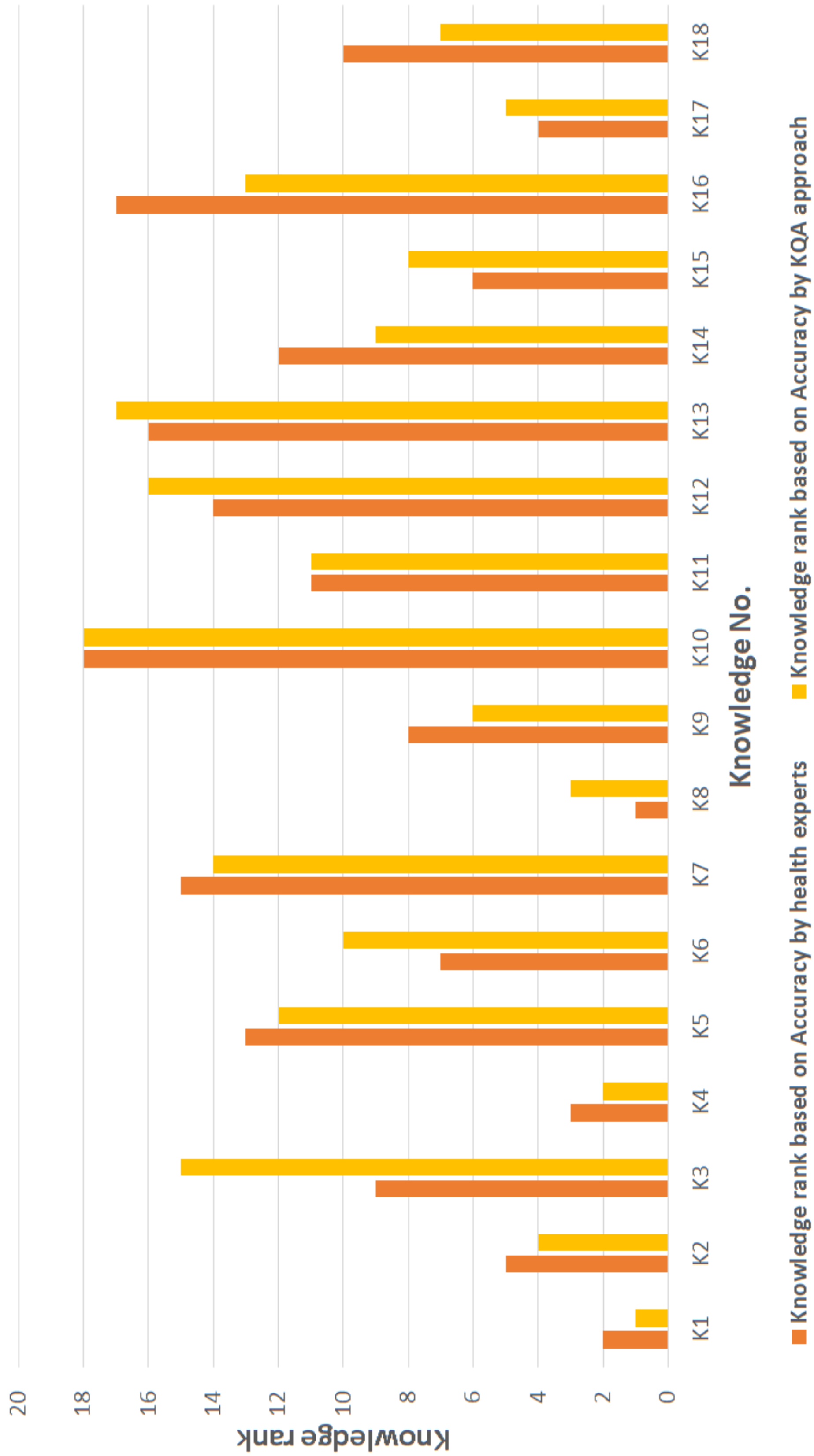


Figure 6.13: Comparing knowledge rank based on accuracy between the KQA approach and health experts

Table 6.15 shows the knowledge rank by KQI score (using the relevancy and accuracy knowledge QMs) compared with the knowledge rank by the health experts in terms of relevancy and accuracy. In this table there are three columns for the KQI_{linear} and $KQI_{weighted}$ ranking results along with ranking results from the health experts. Figure 6.14 illustrates these knowledge ranking results. As seen in the figure, the $KQI_{weighted}$ ranking results are more in line with the health exerts' results when compared with KQI_{linear} . To validate this observation, Spearman's Rank Correlation has been used.

Spearman's Rank Correlation between initial knowledge rank and Knowledge rank by KQI_{Linear} (using relevancy and accuracy knowledge QMs): $p \cong 0.33$

Spearman's Rank Correlation between initial knowledge rank and Knowledge rank by $KQI_{Weighted}$ (using relevancy and accuracy knowledge QMs): $p \cong 0.31$

Spearman's Rank Correlation between initial knowledge rank and Knowledge rank based on accuracy and relevancy by health experts: $p \cong 0.26$

6.5 Principle results

Retrieving high quality knowledge could be a very important contributions to the healthcare domain as low quality knowledge bring about negative consequences for patients' health. In this thesis, the ranking results achieved by knowledge QMs and KQI reveals that the knowledge ranking mechanism in the PubMed search engine (using best match options with Title/Abstract and English language filters) appears to be more based on age of knowledge (from most recent knowledge to the oldest). The PubMed search engine does not fully check other important knowledge QMs such as citation, structure, accuracy and relevancy. In the best match option, the PubMed search engine considers relevancy to find related knowledge to the given query, but, the extracted knowledge is not ranked based on more relevant, mature and accurate knowledge to the given query.

6.6 Chapter Summary

In this chapter, the effect of using different knowledge QMs has been discussed in regard to ranking knowledge. The graphs show the new ranking order compared with the original order extracted from the PubMed search engine. The results achieved by KQI have been assessed by health experts (i.e., clinicians). The majority of the health experts confirm the usefulness of the new ranking mechanism proposed in this thesis. Note that this research is in the early stages and needs to be tested and evaluated in a real-world environment such as a clinic, health centre or hospital (See Section 7.8 of Chapter 7). In the future, it will be expanded to a larger scale and tested by health experts. In this way, there may be refinements to the approach in order to reach peak performance.

Table 6.15: Knowledge rank by KQI and health experts

K No.	**Knowledge rank by KQI_{Linear} (using relevancy and accuracy knowledge QMs)**	**Knowledge rank by $KQI_{Weighted}$ (using relevancy and accuracy knowledge QMs)**	**Knowledge rank based on accuracy and relevancy by health experts**	d **for relevancy and accuracy (by health experts)**	d^2 **for relevancy and accuracy (by health experts)**	d **for** KQI_{Linear}	d^2 **for** KQI_{Linear}	d **for** $KQI_{Weighted}$	d^2 **for** $KQI_{Weighted}$
K1	1	1	3	-2	4	0	0	0	0
K2	4	4	6	-4	16	-2	4	-2	4
K3	17	17	9	-6	36	-14	196	-14	196
K4	2	2	4	0	0	2	4	0	0
K5	9	10	13	-8	64	-4	16	-5	25
K6	8	8	7	-1	1	-2	4	-2	4
K7	12	12	15	-8	64	-5	25	-5	25
K8	3	3	1	7	49	5	25	5	25
K9	5	5	8	1	1	4	16	4	16
K10	18	18	18	-8	64	-8	64	-8	64
K11	11	11	12	-1	1	0	0	0	0
K12	16	16	14	-2	4	-4	16	-4	16
K13	14	15	16	-3	9	-1	1	-2	4
K14	15	14	11	3	9	-1	1	0	0
K15	10	9	5	10	100	5	25	6	36
K16	13	13	17	-1	1	3	9	3	9
K17	7	7	2	15	225	10	100	10	100
K18	6	6	10	8	64	12	144	12	144

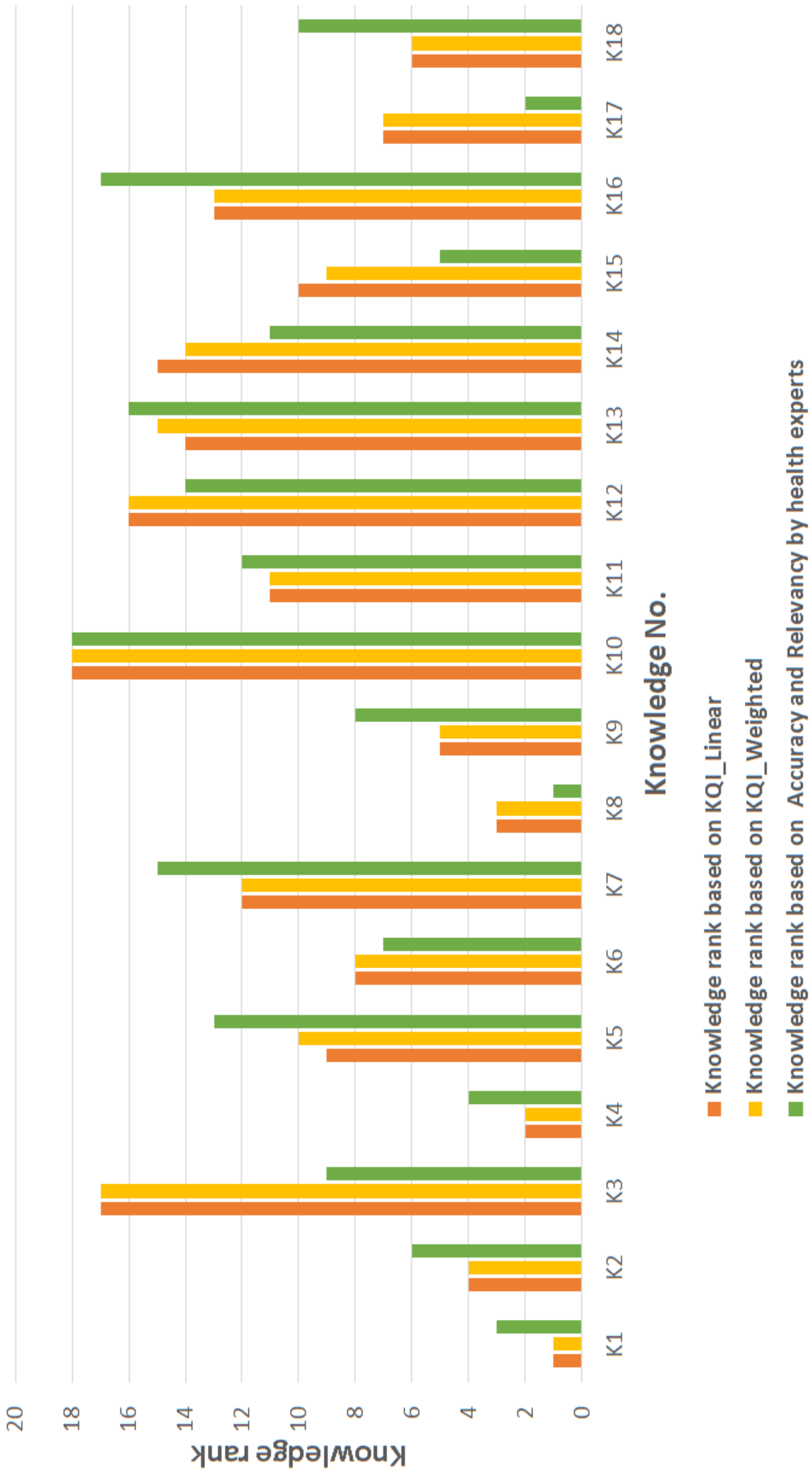


Figure 6.14: Comparing Knowledge Ranking of KQI and health experts' results

Chapter 7

Discussion and Conclusion

7.1 Introduction

The main goal of this chapter is to summarize and explain the contributions of this study. This chapter explains the process of implementing the KQA approach. It explains how this research has answered the proposed research questions. This chapter gives recommendation as to how to upgrade the KQA approach. Finally, the conclusion and future work are explained at the end of this chapter. Note that the list of acronyms used in this thesis has been provided on pages 14 to 16.

7.2 General Discussion

In this thesis, an approach has been proposed to extract and evaluate the quality of knowledge for using in CDSSs. Improvements in knowledge quality have been proposed by reviewing current limitations in the healthcare systems and CDSSs. This issue refers to the lack of clinical knowledge quality assessment for the decision making process. The proposed approach takes advantage of SW technologies, which have been explained in the thesis. The process of extracting knowledge from different KSs and transforming them into an ontological structures has been presented. The generated ontological knowledge will be stored in the central knowledge repository for the further use. The proposed knowledge QMs have also been used to assess the quality of the extracted knowledge from the KSs. In order to validate the approach, the quality of the knowledge was ranked by health experts. The ranked results achieved by the KQA is close to those ranked by the health experts.

Based on a review of related work, there does not seem to be generally accepted existing way to undertake knowledge quality assessment that considers multiple aspects for the ranking process. The KQA approach considers multiple knowledge QMs to identify high quality knowledge for the CDSSs. Search by date tends to hide older knowledge which may be more relevant or of better quality than new knowledge. In fact, it is not always true that new knowledge is better than older knowledge. It is also not always true that structure matching is better than non-structure matching. The following shows how this study has answered the research questions.

7.3 Reflections on the Research Questions

The main goal of this research was to propose and implement a system to discover knowledge from KSs and assess the quality of the extracted knowledge which can serve the CDSSs. The system takes advantage of SW technologies. This thesis aimed to cover the following research questions:

1. What kind of QMs would be useful for assessing the quality of clinical knowledge extracted from knowledge sources?
2. How SW technologies can be used effectively to support CDSSs?
3. Which annotations are useful in improving clinical knowledge for CDSSs using SW technologies?

4. How can QMs be measured to provide high quality clinical knowledge through SW technology?

In the following, each question has been discussed in detail.

7.3.1 Question 1: What kind of QMs would be useful for assessing the quality of clinical knowledge extracted from knowledge sources?

The main objective of this research is to help health experts improve the quality of the decision-making process. To make an effective decision, health experts need to have access to accurate, appropriate and up-to-date knowledge. Therefore, it is vital to extract high quality knowledge to make an intelligent decision. An inappropriate, incomplete and limited knowledge could have a negative impact on a patient's health. In this respect, the proposed approach in this thesis aims to facilitate the process of discovering high quality knowledge. The proposed approach also aims to improve the processes of searching, evaluating, and storing knowledge in the context of the CDSSs.

The knowledge QMs for assessing quality of clinical knowledge have not been previously explicitly discussed in the clinical decision making domain. To identify proper clinical metrics, a questionnaire was conducted in the HINZ and ACHI communities. This questionnaire is attached in Appendix 1. The ranked knowledge QMs obtained by the questionnaire have been considered as knowledge QMs for evaluating the quality of clinical knowledge. This thesis concentrates on evaluating the quality of clinical knowledge by using knowledge QMs in Chapter 5 (i.e., age of knowledge, citation, structure, relevancy, and accuracy). In this thesis, the knowledge quality indicator (KQI) has been proposed to measure and rank the extracted knowledge from the KSs. The KQI adds a particular feature to the knowledge. Using this indicator helps health experts feed confident in their decision making process. The quality of extracted knowledge will be achieved by the proposed knowledge QMs and the assigned KQI.

To review health experts viewpoints, a rating exercise was used to discover which QMs are high priority in the decision making process. In this questionnaire, health experts not only validate knowledge QMs but also provide some suggestions to highlight which QMs are useful and which ones are not effective in improving the quality assessment process.

7.3.2 Question 2: How SW technologies can be used effectively to support CDSSs?

In order to answer this question, a systematic review paper has been conducted with the title of "The issues associated with the use of Semantic Web technology in knowledge acquisition for Clinical Decision Support Systems: A systematic Review of the Literature". This paper has been published in the Journal of Medical Internet Research (JMIR). This paper describes some of the benefits of using SW technologies. Note that the summary of this paper has been mentioned in Sub-subsection 2.6.2.

In this thesis, the benefits of using SW technologies in KA were clearly explained. Figure 2.3 highlights the benefits of applying SW technologies. SW technologies can be used to improve the process of KA.

SW technology and its applications are useful as they can deal with data from multiple sources and facilitate machine-machine communication. The SW is an effort to make knowledge on the Web both human-understandable and machine-readable. There is no need to provide a database schema for sharing data since it has its universal data structure and can be used with many KSs. SW technologies and their features such as semantic interoperability, knowledge integration, and knowledge reuse upgrade and transform old applications into modern and intelligent models (Lozano-Rubí, Pastor &

Lozano, 2014).

To make well-informed decisions, health care applications as well as healthcare professionals need to be able to discover knowledge from many heterogeneous knowledge bases. Having diverse data models and formats has lead researchers to use SW technologies to facilitate the data integration process. SW technologies allow researchers to analyze incompatible biological descriptions in one unified format. For example, using SW technologies helps to mesh datasets about protein-protein interactions to reveal obscure correlations that could assist in formulating promising medications (Feigenbaum et al., 2007).

In the context of knowledge-driven CDSSs, different issues have been improved through utilizing SW technologies, such KA, data collection, and data integration of clinical systems.

7.3.3 Question 3: Which annotations are useful in improving clinical knowledge for CDSSs using SW technologies?

To answer this research question, the useful annotations have been divided into two major categories. The first category are those annotations that represent knowledge quality. These annotations show the scores of knowledge for each knowledge QM and help practitioners feed confident in making decisions. The second category are those annotations which enrich knowledge. These annotations explain concepts and relations and help machines get more information for the decision making process. The way annotations are used explained in detail as follows.

Annotations are a kind of machine-understandable information which can be added to documents. They can also be linked to a particular concept. The annotations and documents can have various formats. As discussed in Chapters 2 and 3, the proposed system has been developed utilising SW technologies. Note that the proposed system takes advantage of ontological structure. The related annotations can be linked to the corresponding concepts, properties and relationships in the ontology to achieve better understanding of the knowledge.

In Chapter 4, the process of creating an ontology using textual documents was explained in detail. As mentioned in Subsection 4.4.1, the extra information (i.e., meta-data/annotations) can be attached to the classes, individuals, and datatype/object properties to enrich the ontology by using annotation properties. It is important to note that using annotation (i.e., meta-data) is as important as using data. They facilitate knowledge quality assessment by providing appropriate information. In Section 5.3, the process of extracting concepts from textual documents and XML files using SNOMED-CT, MESH, and UMLS was explained. In this research, the extracted information related to classes and their individuals will be attached to the ontologies as annotations.

In addition, the information related to knowledge QMs can be attached to the knowledge as annotations. For example, some information like date created, citations, provenance, and locality can be extracted from related tags in XML files. This extra information can be added to the knowledge to be used in the process of measuring age, citation, provenance, and locality metrics. Moreover, the mesh-headings used in the XML files are accessible through a particular link called "has-meshHeading". In this thesis, the mesh-headings as new concepts have been used to enrich the knowledge. The enriched knowledge facilitates the decision making process.

7.3.4 Question 4: How can QMs be measured to provide high quality clinical knowledge through SW technology?

This research question represents how to measure the quality of the knowledge. Chapter 5 explains the related formula and measurements used in this research. Some metrics such as actionable metrics have not been measured in this thesis. The reason behind this is explained in Chapter 5. In Section 5.4, knowledge QMs have been explained through examples. Subsection 5.4.1 discussed the comparison mechanism of extracted knowledge. This mechanism shows how high quality knowledge has been identified through assessing the quality of each knowledge item. In this mechanism, the first knowledge retrieved by the search engine has been considered the main knowledge item and all other knowledge items are compared with this main one. It helps the system to provide unvarying conditions to check the quality of knowledge. In case the system receives a similar query with the existing queries in the repository, the system can use the knowledge related to the stored query as main knowledge, after this other knowledge will be compared with this main knowledge. Section 6.5 explains how the KQI works. As mentioned before, the intrinsic metrics reflect the correct structures. In this regard, the KQI aims to support this fact as well. The KQI also considers the QMs as a new feature for the extracted knowledge. The KQI also aims to represent the adaptability and scalability of knowledge in different systems. Note that the proposed metrics not only attach the related annotations to the knowledge but also enrich the knowledge to make it more effective in the decision making process.

7.4 Thesis contribution

The main objective of this thesis is to propose knowledge QMs which can be used in the decision making process in the healthcare domain. The process of evaluating an ontological knowledge has been clearly explained. Ontologies are the backbone of SW technologies. The benefit of using the ontological structure has been discussed in detail. The KQA approach is proposed in this thesis to assess the quality of extracted knowledge. In this thesis, a basic prototype of the KQA has been developed to be used in CDSSs. The results achieved by the knowledge QMs show that the KQA performs quite well performance in assessing the knowledge quality. The contribution of this thesis are explained below:

- **Identifying knowledge QMs for discovering high-quality knowledge for the decision-making process.**

  These knowledge QMs aim to facilitate the process of assessing knowledge quality for the system. Knowledge QMs have not been considered much in the context of CDSSs. This thesis aims to provide a general view for assessing the quality of clinical knowledge in future. Moreover, practitioners can enrich their personal knowledge through the use of the proposed knowledge in the new generation of CDSSs. The importance of using these knowledge QMs were tested in a questionnaire which is explained in Chapter 5.

- **Proposing and developing the Knowledge Quality Assessment (KQA) to evaluate the quality of extracted knowledge for use in CDSSs.**

  As mentioned earlier, KA has been known as a bottleneck in the CDSSs and there exists no comprehensive system for assessing the quality of clinical knowledge. Therefore, the KQA aims to fill this gap by providing a platform for evaluating knowledge quality that can be used in the CDSSs.

- **Proposing the possibility of assessing knowledge quality through the use of computerized approach.**

  One of main goals of this thesis is to identify some formula for assessing the quality of clinical knowledge. To answer the third research question, this thesis demonstrates that it is possible to assess and identify high-quality knowledge through a propose computerized approach.

- **Representing the benefits of using SW technologies that provide an intelligent structure for representing, sharing, storing, and analysing knowledge in CDSSs.**

In Section 2.6, the benefit of using SW technologies in CDSSs was explained in detail. This section also explains how SW technologies remedy the common issues occurring in the CDSSs. Figure 2.3 shows some possible SW-based approaches which could be used to improve the performance of CDSSs.

- **Taking advantage of annotations (i.e., meta-data) as one of the main features of SW technologies.**

  These annotations are attached to enrich knowledge and subsequently improve the process of knowledge quality assessment.

- **Proposing an ontological structure for representing clinical knowledge.**

  It is important to mention that storing knowledge in the ontological structure empowers the system to represent concepts and their relationships as classes and links. This structure is a kind of machine-understandable and human-readable structure.

7.5 Thesis Limitations

Some of this thesis's limitations are briefly explained.

The system is not complete, as it does not use all the identified knowledge QMs. This research was to provide a proof of the knowledge quality concept for clinical decision-making and to demonstrate that the approach taken is feasible. It also reveals the KQA approach and shows how KQA can incorporate with CDSSs. There exist some knowledge QMs proposed by participants (refer to Section 5.3) which have not been considered in the system. Some of these knowledge QMs are subjective and some objective. For example, Risk of Bias (RoB) could be used as a measure of quality. This is a statistical tool involved with meta analysis (Higgins et al., 2011). The process of defining and measuring these knowledge QMs requires more technical study. It is also important to note that these knowledge QMs need to be developed in a computerized-based approach to be compatible with the ontological structure of knowledge used in this thesis.

There are also some limitations in applying SW technologies to the systems such as CDSSs. Apart from using and managing personal data and knowledge, the privacy issues around using SW could be a significant problem in such systems. One of the reasons is that everything published through SW technologies will be shared and accessible to the public. This fact brings up some privacy issues in the context of CDSSs. Another issue that can be problematic for applying SW technologies can be resource requirements to support the complete features of SW. The SW technology may need some specific resources to work, however, some of them may not exist in the current environment. There is a need to change and update the information society and economy based on the SW-based approaches.

Another limitation for this thesis is related to the types of KSs. Some of them are more faster than others. As a proof of concepts, the KQA system tested with PubMed KS. In the future, weighting of different KSs should be consider for the performance of CDSS.

7.6 Thesis Recommendation

Knowledge quality assessment is known to be a critical issue in the healthcare domain and it needs to be added to the CDSSs as an essential feature. Knowledge quality assessment is not only to be used in the healthcare domain but also in other domains. Therefore, it is necessary to propose an intelligent mechanism to handle this issue. This thesis has proposed a system to assess the quality of extracted knowledge. This thesis also shows how this system can be developed and implemented for using in the healthcare domain. In this thesis, an ontological structure has been proposed to be used in the KQA to store and represent clinical knowledge. One of the main benefits of ontology is that it facilitates the evaluation process by providing a machine-understandable structure.

In order to improve and develop the KQA, this section discusses a new ontological structure called reflexive ontology that can be useful for the process of knowledge reuse. This structure also facilitates the process of storing information for the further use (e.g., the search process). In this respect, the reflexive ontology could be used as a structure in the central knowledge repository of the KQA. The reason behind such a suggestion is that this structure is able to store high quality knowledge along with the related query in its structure. Such stored information could facilitate the decision making process. As mentioned in Chapter 3, there exist a central knowledge repository inside the KQA that stores extracted knowledge along with the related queries. The reflexive ontology supports the requirements of the central knowledge repository. The process of using the reflexive ontology inside the KQA has been explained as follows.

The reflexive ontology proposes a particular schema for storing ontological knowledge (i.e., classes and related individuals) along with related queries. It is important to mention that this structure provides the capability to update knowledge along with related queries in different timeframes. Toro, Sanín, Szczerbicki and Posada (2008) suggested that the reflexive ontology is able to generate new knowledge. More precisely, it is able to interpret knowledge along with the queries to generate new rules (i.e., new knowledge) that can be used in the decision making process. It is important to note that this type of ontology has not been used in any healthcare system (e.g., CDSSs). Therefore, considering reflexive ontology could provide a new avenue for developing healthcare systems (e.g., CDSSs).

Figure 8.1 depicts the structure of a reflexive ontology. As seen in the figure, the extracted knowledge along with related queries have been transformed into the ontological structure and stored as a reflexive ontology. Note that the figure only shows the relationships between knowledge and queries in the reflexive ontology. As mentioned, the queries have been attached to the related knowledge. In cases where similar queries are queries, the system can easily uses the stored knowledge. This task reduces searching time and improves performance of the system. Storing queries inside the ontologies also supports reasoning ability. The reasoned knowledge can enrich schema level knowledge as well.

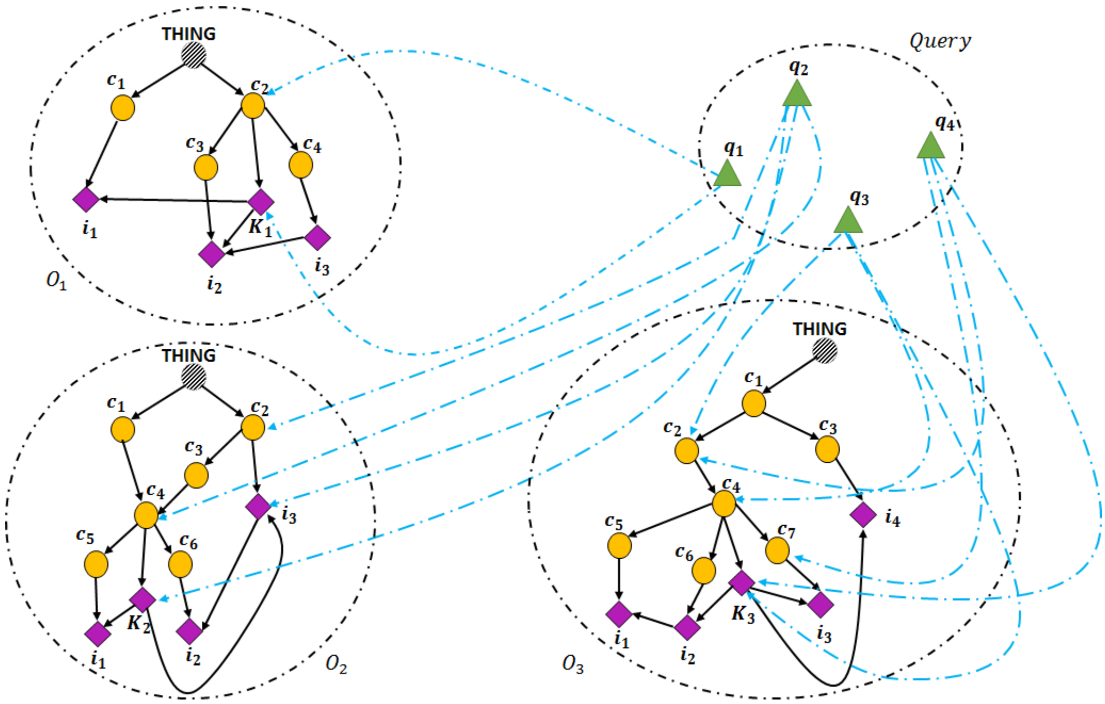


Figure 7.1: A sample of reflexive ontology

In this mechanism knowledge has been enriched in three different ways: (1) adding information, (2) updating information to knowledge, or (3) deleting information. When there is new information about the knowledge item in the healthcare domain and this information is not in the knowledge item, it will be added to the knowledge item. The knowledge will be updated when the related information changed. Lastly, if information about the knowledge item is no longer matched with the query, it will be deleted from the knowledge item.

Another possible option is to propose a recommender system that facilitate the communication between practitioners and the healthcare system. Such systems recommend high quality knowledge to practitioners. A practitioner is also able to confirm the quality of the delivered knowledge if it is compatible with his/her knowledge. The confirmed knowledge will then be stored in the repository for the further use.

It is also possible to develop the proposed system to collect and store queries. In this case a particular structure needs to be proposed inside the query interface backend. In case of receiving a query, it can be transformed into the ontological structure automatically to facilitate the process of knowledge discovery.

7.7 Thesis conclusion

Decision making is one of the main activities of any health expert. In order to assist human decision making, the CDSSs are developed to facilitate health care systems. As discussed throughout this thesis, a CDSS is a specific type of decision support system that helps health experts in decision making activities with electronically stored clinical knowledge. Due to a lack of knowledge quality assessment in the healthcare systems, in this thesis, a computerized approach, knowledge quality assessment (KQA) has been proposed to discover and evaluate clinical knowledge for the CDSSs. Based on the systematic research conducted on related work in this domain, it appears recent CDSSs suffer from a lack of quality assessment of the extracted knowledge from healthcare online search engines. For example, PubMed is one of the most popular online search engines that helps health experts in the decision making process. The process of checking the quality of knowledge requires multiple factors to identify and extract high quality knowledge from KSs. The proposed approach in this thesis applied multiple knowledge QMs to enhance the quality of the search process.

In this thesis, different types of CDSSs along with their related issues in KA have been reviewed in Chapter 2. Some recent methods applied in the CDSSs are also noted in this chapter. The advantages of utilizing SW technologies are discussed. One of the main reasons to review SW technologies is to assess how it improves common issues in KA for CDSSs. Based on the research in this thesis, SW technologies have a huge potential to enhance KA issues in CDSSs. Chapter 2 also highlights the necessity of knowledge quality assessment in the decision making process. A few popular QMs are also introduced in this chapter. Chapter 3 explains the research design and the structure of the whole system. The KQA framework along with its components are explained. The process of extracting knowledge from KSs and transforming it into ontological structure are elucidated in Chapter 4. The process of knowledge quality assessment have been illustrated in Chapter 5. By running a questionnaire among healthcare experts, some candidate knowledge QMs are identified and introduced in Chapter 5. Note that the knowledge QMs with the highest priorities were selected from the questionnaire. The process of defining and measuring the knowledge QMs are also discussed in Chapter 5. KQA was tested on real world sources to check its performance in detecting high quality knowledge. The experimental results indicate the effectiveness of the KQA in discovering high quality knowledge.

7.8 Future Work

The thesis presented here deals with the problem of KA in CDSSs. With the growing amount of clinical health data over the Web, it is essential to access quality knowledge from KSs. This thesis proposed a computerized approach to evaluate the quality of clinical knowledge discovered from KSs. The proposed knowledge QMs are identified from related research. The knowledge QMs are also validated by health experts through a questionnaire. The proposed approach takes advantage of SW technologies to facilitate and improve the process of extracting high quality knowledge from KSs. The experiments performed on a real world KS (e.g. PubMed) demonstrates the effectiveness of the proposed approach. In the following, some future directions have been set forth to improve the approach presented in this thesis.

- **More investigation for measuring the proposed knowledge QMs as well as knowledge QMs which have not been considered**

  Although some techniques were proposed to measure some knowledge QMs such as age of knowledge, citation, structure, accuracy, and relevancy, the question is whether there exist better techniques to measure these knowledge QMs. Moreover, some of other knowledge QMs suggested by participants in this thesis need to be considered, for example, reliability was one the top metrics identified from by questionnaire. This knowledge QM was not considered. As future work, the related measure for implementing reliability could be proposed to improve knowledge quality assessment for the CDSSs. The proposed knowledge QMs could be assigned to the knowledge quality assessment if there exists a computerized approach that can be applied to the system.

- **Improve and develop the smart knowledge browser**

  As part of this work, a project funded and supported by the Precision Driven Health (PDH) organization was developed to show the effectiveness of the smart knowledge browser for testing on real world sources. The aim of the project was to build a browser which is able to discover the high quality knowledge in terms of relevancy. In the thesis, some of the other knowledge QMs were checked and applied for assessing quality of knowledge. For future work, more knowledge QMs need to be added to assess the knowledge quality in the knowledge browser. The browser can also be developed with consideration of the reflexive ontology structure to store user queries for further use. Another way to improve the knowledge browser is to transform queries into an ontological structure to speed up the search mechanism.

- **Improve and develope the semantic search for unstructured clinical data**

  A vast amount of healthcare data is unstructured and impervious to automated searching. This means that health experts waste time manually searching through subsets of the patient record. Clinical workflow and health outcomes cannot improve until they have access to all the information via a fast and semantic search function. This thesis aims to improve current clinical workflow and health outcomes through evaluation and application of semantic search capabilities to unstructured clinical narratives using SW technologies. Applying semantic search capabilities to clinical data would assist in reducing clinical effort and search time resulting in better, more timely healthcare outcomes and cost effectiveness.

- **Implementing the proposed approach in a real-world scenario**

  Current CDSSs suffer from a lack of knowledge quality assessment for the decision making process. This thesis proposes a novel approach to improve this process by employing the knowledge QMs. The proposed approach is still in the early stages and needs to be implemented and tested in a real-world scenario (i.e., healthcare organization). By implementing the approach on a larger scale different aspects (e.g., components/QMs) might need to be redesigned to meet requirements. The proposed approach aims to be designed and tested in the healthcare organization to verify its performance. Moreover, it could use alternative methods for CDSSs such as using knowledge from EHR (rather than literature) or from clinical guidelines. The alternative CDSSs are different types of CDSSs explained in Chapter 2, Section 2.2.1. In this section, Info-buttons, Bramching Logic, Probabilistic Systems, Rule-Based Systems, Ontology-driven and Data-driven CDSSs are types of CDSSs that can be used as an alternative

CDSS to work with EHR, clinical guidelines and data.

- **Measuring trust in KSs**

  It is important to note that trust in KSs may be important in the healthcare domain. In this case, the system needs to consider this factor in KSs. The process of measuring trust in KSs could be a future work of this thesis.

In addition, a number of still-open questions have been identified for future investigation:

1. Does the rank of knowledge quality correspond with expert judgement for different domains ? This requires many users and domains to test.

2. Can the system be made automatic? This requires large-scale trials using real or simulated patient data in a CDSS to see whether knowledge from this approach improves patient outcomes.

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Appendix A

Ethics Approval

This appendix contains the ethics approval letter received from the AUCKLAND UNIVERSITY OF TECHNOLOGY ETHICS COMMITTEE (AUTEC)

AUTEC Secretariat

Auckland University of Technology

D-88, WU406 Level 4 WU Building City Campus

T: +64 9 921 9999 ext. 8316

E: ethics@aut.ac.nz

www.aut.ac.nz/researchethics

25 September 2015

Dave Parry

Faculty of Design and Creative Technologies

Dear Dave

Ethics Application: **15/350 Discovery of high-quality knowledge for clinical decision support system by applying semantic web approaches.**

Thank you for submitting your application for ethical review to the Auckland University of Technology Ethics Committee (AUTEC). I am pleased to confirm that your ethics application has been approved for three years until 24 September 2018.

As part of the ethics approval process, you are required to submit the following to AUTEC:

- A brief annual progress report using form EA2, which is available online through `http://www.aut.ac.nz/researchethics`. When necessary this form may also be used to request an extension of the approval at least one month prior to its expiry on 24 September 2018;

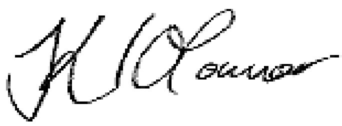
- A brief report on the status of the project using form EA3, which is available online through `http://www.aut.ac.nz/researchethics`. This report is to be submitted either when the approval expires on 24 September 2018 or on completion of the project;

It is a condition of approval that AUTEC is notified of any adverse events or if the research does not commence. AUTEC approval needs to be sought for any alteration to the research, including any alteration of or addition to any documents that are provided to participants. You are responsible for ensuring that research undertaken under this approval occurs within the parameters outlined in the approved application.

AUTEC grants ethical approval only. If you require management approval from an institution or organisation for your research, then you will need to obtain this. If your research is undertaken within a jurisdiction outside New Zealand, you will need to make the arrangements necessary to meet the legal and ethical requirements that apply there.

To enable us to provide you with efficient service, we ask that you use the application number and study title in all correspondence with us. If you have any enquiries about this application, or anything else, please do contact us at ethics@aut.ac.nz.

All the very best with your research,



Kate O'Connor

Executive Secretary

Auckland University of Technology Ethics Committee

Cc: Seyedjamal Zolhavarieh szolhava@aut.ac.nz

Appendix B

Questionnaire materials for knowledge quality metrics rating and validation by health experts

This appendix presents materials that received ethical approval and were used for rating and validating quality metrics among health experts. These were:

- Participant Information Sheet
- Rating Exercise Form
- Demographic Information Collection Form

B.1 Participants Information Sheet

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Date Information Sheet Produced:

17 Sep. 15

Project Title

A study to validate metrics for quality of clinical knowledge in Clinical Decision Support System

An Invitation

Hello,

I am a PhD student at Auckland University of Technology (AUT), Auckland, New Zealand. I am working on using Semantic Web technology in Clinical Decision Support Systems (CDSSs) to extract and support high quality knowledge for decision making to conduct my PhD in Computer Science under supervision of Assoc. Prof. Dave Parry.

In order to identify high-quality knowledge for clinical decision support systems we need to identify what makes "high quality" knowledge by means of knowledge Quality metrics. Some candidate knowledge quality metrics that are useful for knowledge and system performance have been collected in this study. To understand the importance of these knowledge quality metrics, we are asking you validate them by participating in our questionnaire. This questionnaire is based around rating potential knowledge quality metrics.

What is the purpose of this research?

The purpose of this research is to validate the quality measures for assessing clinical knowledge for Clinical Decision Support System as part of my research in conducting my PhD in Computer Sciences. The results will be published and presented in academic publications/presentations.

How was I identified and why am I being invited to participate in this research?

You are invited as someone interested in health informatics. Those who have knowledge about Clinical Decision Support System are particularly welcome. This questionnaire is anonymous and there is no need to write your contact details.

What will happen in this research?

Decision making is an essential activity for clinicians in the healthcare domain. Experts play an important role in decision making. However, experts may make a wrong decision, or not be available to make the decision. To this end, informatics researchers have proposed many methods to extract clinical knowledge using computers for the purpose of decision making. A well-known approach in this field is Clinical Decision Support System (CDSS). The CDSS improves the level of decision making. The knowledge used in the CDSS must be both up to date and relevant for the cases that are being presented to it. Obviously, inappropriate knowledge can have negative influence on decision making. Finding the latest accurate clinical knowledge is difficult since knowledge is changing rapidly and it might be proposed by different organizations in different formats. To the best of our knowledge, the quality of proposed knowledge using CDSSs has only been considered to a minor extent. This study aims to propose a model for assessing the quality of extracted knowledge to support better decisions. To assess knowledge quality, we need some knowledge quality metrics to evaluate it. This questionnaire aims to ask health experts (i.e. health informatics scholars and practitioners) to rate knowledge quality metrics and validate the candidate knowledge quality metrics that can be useful for this research.

What are the benefits?

The potential benefit of this research is to allow me to complete my PhD and potentially enhance the human decision making by identifying knowledge quality metrics.

How will my privacy be protected?

The questionnaire is anonymous and you will not be identified.

How do I agree to participate in this research?

You will not need to complete a consent form. You can agree to participate by completing questionnaire in an online questionnaire in a public URL.

Will I receive feedback on the results of this research?

Yes, Results will be put in a public URL and published via the HiNZ conference in 2016.

You may also contact me or my supervisor at a later date, using the details below, for a summary of findings.

What do I do if I have concerns about this research?

You are under no obligation to accept this invitation. If you decide to participate you have the right to:

- Decline to participate
- Ask any question of myself or my supervisor about the study at any time during participation.

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, Assoc. Prof. Dave Parry, dparry@aut.ac.nz, +6499219999 xtn 8918.

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, Kate O'Connor, ethics@aut.ac.nz , 921 9999 ext 6038.

Whom do I contact for further information about this research?

Researcher Contact Details:
Seyedjamal Zolhavarieh
PhD Candidate
School of Computer Science
Auckland University of Technology (AUT)
Auckland 1142, New Zealand
Mob: +64210474720

szolhava@aut.ac.nz

Project Supervisor Contact Details:
Assoc. Prof. Dave Parry
School of Computer Sciences
Auckland University of Technology (AUT)
Auckland 1142, New Zealand
+6499219999 xtn 8918
Fax 649921 9944

dparry@aut.ac.nz

Approved by the Auckland University of Technology Ethics Committee on 25 September 2015, AUTEC Reference number 15/350.

B.2 Rating Exercise Form

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Rating Exercise Form

By doing this questionnaire you indicate your consent to participate.
These questions are about rating and validating knowledge quality metrics for clinical knowledge extracted from knowledge sources (e.g. PubMed, guidelines, and text books) that are used for decision making and Clinical Decision Support System (CDSS).
Please rate the following knowledge quality metrics based on their importance from 1 to 5 where:

- 1: not at all important
- 2: slightly important
- 3: moderately important
- 4: quite important
- 5: extremely important

If metrics are not applicable, please select the N/A.

Knowledge quality metric	**Description**	**Rating**
Accuracy	How accurate the knowledge is.	1 2 3 4 5 N/A
Reliability	The knowledge source will produce the same answer for the same question in different knowledge sources.	1 2 3 4 5 N/A
Timeliness	The knowledge source produces an answer in an appropriate time.	1 2 3 4 5 N/A
Age of knowledge	It indicates how old the knowledge is.	1 2 3 4 5 N/A
Provenance	The knowledge should be based on valid authority.	1 2 3 4 5 N/A
Locality	It is located to the location that knowledge created.	1 2 3 4 5 N/A
Relevancy	The knowledge contains relevant information to support the user query.	1 2 3 4 5 N/A
Citation	It illustrates the number of citing, referring, and quoting knowledge used for different purposes.	1 2 3 4 5 N/A
Structure	In order to analyse the quality of knowledge, it is better to represent its structure in the machine understandable format(E.g. XML and OWL). One of the existing method is to represent knowledge in the ontological structure to facilitate the process of knowledge assessment.	1 2 3 4 5 N/A

Which knowledge quality metric is least important? . . . .
Which metric is most important? . . . .
Is there any knowledge quality metric that you think it might be useful for CDSS which is not addressed? . . . .

Any other Comment:

B.3 Demographic Information Collection Form

AUT

TE WĀNANGA ARONUI
O TĀMAKI MAKAU RAU

Please circle the age bracket that you belong to:

- 20-29
- 30-39
- 40-49
- 50-59
- 60-69

How confident are you in using Clinical Decision Support System? (Please select one)

conteExtremely confident 10 9 8 7 6 5 4 3 2 1 not at all confidentnt...

How much you think computer-based systems can be useful in human decision making? (Please tick one)

- Extremely useful
- Quite useful
- Moderately useful
- Slightly useful
- Not at all useful

Approved by the Auckland University of Technology Ethics Committee on 25 September 2015, AUTEC Reference number 15/350.

Appendix C

Summary of Literature Review

The following table illustrates a brief summary of the literature review of that has done for literature review chapter.

Paper	Problem	Goal	Method	Strength(s)	Weakness(s)
Semantic Web technologies for Healthcare Systems					
Semantic Web for Health Care and Life Sciences: a review of the state of the art (Cheung et al., 2009)	Inconsistency in naming and heterogeneity in data models and formats	Review on role semantic web in healthcare			
Is semantic web technology ready for healthcare? (Wroe, 2006)	Lack of productive and semantic clinical data in the healthcare system	Manipulating semantically rich and highly structured clinical data	Using semantic web technology	Adoption of semantic web technology	Knowledge representation by using semantic web technology
Developing a semantic Web services for interoperability in diabetic healthcare (Bai & Zhang, 2005)	Adoption of dynamic factors and diversities	Interoperability between healthcare actors	Embryonic prototyping approach (EMA) in IMIs project	Self-learning infrastructure / start small and grow	Limited Semantic Web, lack of the relationship validity
The need for semantic web service in the eHealth (Della Valle et al., 2005)	Lack of semantic interoperability	Semantic interoperability between heterogeneous systems	Use of mediators, semantic web services	Good ontology representation	Layering in some semantic web service
Knowledge-based patient data generation (Huang, van Harmelen, ten Teije & Dentler, 2013)	Accessing required patient data as realistic as possible	To make the generated patient data as realistic as possible	Advanced patient data generator (APDG): using domain knowledge to control the data generation process, patient data definition language (PDDL)	Convenient and flexible generation	Only support RDF formats
A Semantic Web management model for integrative biomedical informatics (Deus et al., 2008)	The need for distributed and evolvable representations for system biology	Delivering the desired futures of distribution and evolvability	S3DB core, a semantic web model for data representation (RDF representation)	The consequences of semantic integration	Requires encapsulation of the data

Using the rhizomer platform for semantic decision support systems development (García, 2012)	Lack of data integration and the user interact	Facilitating user interaction and data integration	Rhizomer, semantic web based framework for data publishing and user interacting	Dynamic integration of data	Small range of data integration, weak annotation
Using semantic web technologies for cohort identification from electronic health records for clinical research (Pathak et al., 2012)	Lack of data integration and cohort studies	To accurately identify subjects for inclusion in cohort studies and investigate federated data integration	Using Resource Description Framework (RDF) to identify subjects	Execute complex queries	Using particular database not general
Rule-based Semantic Web services annotation for healthcare information integration (Sonsilphong, Arch-int & Arch-int, 2012)	Semantic interoperability (lack of the uniform system and an accepted standard)	To facilitate maximal annotation and dynamism in web services discovery, selection, composition, and monitoring	Broker-based model semantic interoperability for data integration (SIDI)	Web service Annotation, Ontology mapping and composition of web services	Representing data in a sufficient way
Semantic Interoperability for data integration framework using semantic web services and rule-based inference: A case study in healthcare domain (Sonsilphong & Arch-int, 2013)	Interoperability of the data exchange and between heterogeneous systems	To automatically construct the semantic rule-based inference	A broker based model semantic interoperability for data integration	Web service Annotation, Ontology mapping, Composition of web services	Representing data in a sufficient way
SHARE: A Web Service-Based Framework for Distributed Querying and Reasoning on the Semantic Web (Vandervalk, McCarthy & Wilkinson, 2013)	Crucial infrastructure for querying or reasoning across distributed data sources	Simple extensions to query engines and reasoners	SHARE, a semantic web service-based framework	The ability to automatically "lift" raw data into an ontology	It is dependable (depends on access to a large central registry of annotated services with appropriate predicates)

Process interoperability in healthcare systems with dynamic semantic web services (Khan et al., 2013)	Complexity of healthcare systems because of extreme heterogeneity	Timely delivery of healthcare services	Dynamic semantic web service, web service Modeling Framework (WSMF), Health Life Horizon (HLH)	Cost-effective, flexible, and interoperable solution	Requires semantic mapping
How Ontologies Can Improve Semantic Interoperability in Health Care? (Schulz & Martínez-Costa, 2013)	Semantic interoperability for managing various clinical data	Having an improved interoperability of clinical data	Transforming existing resources into “semantically enhanced ones by applying OWL DL expression."	The allowance of DL reasoning to compare different distributions of content in OWL-DL	Weak DL reasoning with a significant amount of instance data
A Semantic Web Services for Medical Analysis using the OWL-S Language (Fayçal & Mohamed, 2011)	Lack of automatic medical analysis system	Improve medical analysis to increase the quality of care	Semantic web service based on OWL language	Automatically web service without human intervention	Ontology of medical analysis needs more importance to make machine understandable web service
Knowledge Representation in Semantic Web-based Healthcare Systems					
A model-driven approach for representing clinical archetypes for Semantic Web environments (Martínez-Costa, Menárguez-Tortosa, Fernández-Breis & Maldonado, 2009)	Different standards for representing and exchanging EHR information	Representing archetypes	Semantic Web and model-driven engineering technologies	Shareable and reusable archetypes, availability of resources	Poor maintenance properties
A semantic-web oriented representation of the clinical element model for secondary use of electronic health records data (Tao et al., 2013)	Lack of semantic definitions to perform reasoning and consistency	Providing authoring, reasoning, and querying tool	Clinical Element Model (CEM) using the web ontology language (OWL)	Accurate transformation of the CEMs	Hard to automatically make the distinction

Supporting Computer-interpretable Guidelines' Modeling by Automatically Classifying Clinical Actions (Minard & Kaiser, 2013)	Modeling computer-interoperable clinical practice guidelines	To classify activities according to the clinical actions	Rule-based approaches and machine-learning	Two steps method using SVM classifiers is better than 1-step classification	Less validation / less workload
Implementation of a System for Intelligent Summarization of Longitudinal Clinical Records (Goldstein & Shahar, 2013)	Existing an enormous amount of time-oriented patient data for decision-making	To demonstrate the feasibility of creating a system that can generate a sophisticated knowledge- based textual summary of arbitrary long time-oriented clinical data	cliniText, combination of knowledge-based temporal abstraction, textual summarization, abduction, and natural language generation	Pruning redundant data/ uniformly high level of abstraction	Just original text/ they cannot avoid wrong text when they have bad data

Knowledge Acquisition

Knowledge acquisition: Past, present and future (Gaines, 2013)	Need to be able to recognize and utilize what we did not expect as much as we also need to strive particular objectives by particular means.	To review progress in knowledge acquisition techniques	Literature Review		
Mining electronic health records: towards better research applications and clinical care (Jensen et al., 2012)	technical challenges of integrating scattered, heterogeneous data, also to ethical and legal obstacles that limit access to the data	Analyzing large amounts of patient data for establishing new patient stratification principles and for revealing unknown disease correlations	data-driven knowledge discovery on cohort-wide health data via genotype-phenotype relationships	true data interoperability and mining mechanism if EHR is sufficient (although, most of the times it has random errors in large data sets)	EHR data are subject to random errors and systematic biases. Heterogeneous data

Knowledge Quality and Quality Metrics

OntoQA: Metric-Based Ontology Quality Analysis (Tartir et al., 2005)	determining suitable ontology	demonstrate the applicability of ontologies by evaluation of several ontologies using different metrics	OntoQA, an approach to analyze ontology	using well-defined metrics to analyze the quality of the ontology	Lack of large size schema for ontology, subjective task
Knowledge Quality and Quality Metrics in Knowledge Management Systems (Tongchuay & Praneetpolgrang, 2008)	Inaccurate measurement criterions for knowledge quality	To present the conceptual framework for creating standards for quality of knowledge in knowledge management systems.	Qualitative and quantitative methodology / conceptual framework for knowledge quality		
Improving Quality of Ontology: An Ontology Transformation Approach (Mostowfi & Fotouhi, 2006)	evolutionary change in the database schema	to improve the quality of ontology and database schema	a set of Schema Transformations	Using subjective, informal criteria to the general improvement in quality without quantifying them.	Lack of syntactic and semantic quality improvements
ONTOMETRIC: A method to choose the appropriate ontology (Lozano-Tello & Gómez-Pérez, 2004)	determining the most appropriate ontologies for the new system	to measure the suitability of existing ontologies	ONTOMETRIC, multilevel framework to assess ontologies based on Analytic Hierarchy Process	helps to justify the decision taken in a particular ontology	it is entirely subjective
Ontology quality by detection of conflicts in metadata (Arpinar et al., 2006)	improvement of ontology quality	the detection of conflicting information (within an ontology) as a criterion to improve the quality of an ontology	a rule-based approach by which human experts can define conditions that signal a conflict in data	a flexible method in a populated ontology	increasing the amount of memory required to hold the knowledge base and limitation of scalability of the approach when many facts and rules represent

A semiotic metrics suite for assessing the quality of ontologies (Burton-Jones et al., 2005)	interpreting and reasoning with semantics	to present a suite of metrics that can be used to evaluate the quality of ontologies	Operationalize the metrics and implement them in an "ontology auditor."	formal ontologies emphasize the high level, philosophical issues rather than pragmatic issues	metrics and concepts that are applicable may have limited usefulness in any one application
The quality of knowledge: Knowledge patterns and knowledge refactorings (Rech et al., 2007)	how to describe, structure, interrelate, group, or manage knowledge	to structure knowledge in knowledge management systems in the form of so-called knowledge patterns, to stimulate the discussion about the meaning of quality in the context of KM	transferring the concept quality, and refactoring from software engineering to the field of KM	The helpful concept of patterns and anti-patterns for documenting knowledge and experience, The presenting quality model for knowledge	several of the patterns described might not be applicable or be misleading in a particular context or other cultural backgrounds
Clinical Decision Support System (CDSS)					
Challenges in developing effective clinical decision support systems (Sartipi et al., 2011)	challenges in effective and efficient decision-making process	outlining different aspects and problems of providing effective clinical decision support systems	Literature Review		
Clinical decision-support systems (Musen et al., 2014)	computer-based decision aids	To provide motivation for computer-based decision aids	Literature Review		
Semantic Web-based CDSS					
A Knowledge-based Clinical Decision Support System for the diagnosis of Alzheimer Disease (Sanchez, Toro, Carrasco, Bonachela et al., 2011)	Lack of supporting early diagnosis	Early detection of Alzheimer disease (AD)	Knowledge engineering (KE) diagnosis support tool by using ontologies and semantic reasoning	Using ontology and multi-disciplinary knowledge gathered	Limited range and validated domain

SemanticDB: A Semantic Web infrastructure for clinical research and quality reporting (D Pierce et al., 2012)	Reliability of research findings, trust of investigation and administrators, accuracy of quality metrics	To create a data management system with sufficient flexibility and extensibility	content repository, the query interface, data production pipeline	supporting clinical research and quality of care measurement, reducing the burden of duplicate effort, imposing transparency and consistency to reduce errors in the reported data	ontology alignment with current medical practice, performance has been adequate but not stellar, maintaining semantic alignment, difficulties in using inference rules in clinical data
A Universal Clinical Decision Support System using semantic web services (Hederman & Khan, 2012)	Achieving a universal clinical decision support system, problem with standalone CDSS	To develop a semi-automated approach to discover, select and compass CDSSs available as web services	a SWservice framework	Proposed high-level vision of CDSS using SW services	lack of identifying the kinds of formalized semantics attended to the services that are useful in clinical and CDSS, need to be implemented and validated
SemanticCT: A Semantically-Enabled System for Clinical Trials (Huang, Ten Teije & Van Harmelen, 2013)	Lack of integration and semantic interoperability among clinical trials	To achieve interoperability/ to facilitate automatic reasoning and data processing services for CDS	SemanticCT based on LarKC platform with reasoning supported by SWRL in Prolog	Faster identifying eligible patients	Prolog SWRL has limited functionalities for data processing
Semantic web framework for knowledge-centric clinical decision support systems (Hussain et al., 2007)	Lack of knowledge-centric system for decision-making	Computerize clinical practice guidelines (CPG)	Semantic web framework for CDSS	Integrating multiple ontologies	Lack of validation for knowledge / limited domain
Exploiting OWL reasoning services to execute ontologically-modeled clinical practice guidelines (Jafarpour et al., 2011)	Lack of exploiting reasoning services to run the CPG	To present CPG execution approach that leverage OWL reasoning services to execute CPG	OWL-based approaches/ Graph traversal based execution engine	A comprehensive and sound execution environment	

BioDash: a Semantic Web dashboard for drug development (Neumann & Quan, 2005)	How to include beliefs, such as models and hypotheses into a standard database for decision-making. / sharing heterogeneous knowledge, experimental data, and interpretations in meaningful ways that go beyond transmitting data fragment	To aggregate heterogeneous yet related facts and statements (using on RDF model) into an intuitive, visually descriptive and interactive display.	SW technology based on RDF and OWL (SW discovery)	capability of data integration/ allowing users to incorporate data from custom data sources	standard do not exist yet for semantic lenses/ lack of model for aggregation or knowledge sharing/ memory limitation
Cocoon glue: a prototype of wsmo discovery engine for the healthcare field (Della Valle & Cerizza, 2005)	Integration of many complex technologies with the existing regional eHealth services	reducing medical error/ developing on efficient system for the management of the web services that would include publishing, discovery, and composition of services	Web Service Modelling Ontology (WSMO) with an open source f-logic inference engine called Flora 2	clear separation between the ontologies/ speeds up the gathering of consensus/ good trade-off between expressiveness and performances	the way to transform existing terminologies like ICT into ontologies, the subset of f-logic is to restricted for describing similarity
Artemis: Deploying semantically enriched Web services in the healthcare domain (Dogac et al., 2006)	Interoperability problem	To describe the web service functionality semantics/ To describe the meaning associated with the message or documents exchanged through web services	Using OWL language	To provide interoperability in the healthcare domain/ identify need to semantic annotation	Billing and insurance
A framework for personalized decision support system for the healthcare application (Muthuraman & Sankaran, 2014)	Personalized treatment in healthcare systems	To provide personalized treatment flow without the intervention of domain experts	Fuzzy decision tree, fuzzy rules, SWRL	User-friendly environment/ Dynamic process/ Good performance on memory/ Reduce the required time of care	Work in a specific domain

Using OWL ontologies for adaptive patient information modeling and preoperative clinical decision support (Bouamrane et al., 2011)	Design and implementation of a knowledge-based preoperative decision support system	Developing a system capable of supporting health professionals in secondary care during the preoperative assessment of patient before elective surgery	Molecular ontologies developed in OWL, the OWL API and an automated logic reasoned	Tailor patient information collection according to individual medical context/ Efficiently manage a vast repository of preoperative assessment domain knowledge	The collected information directly from the patient is likely to be "cross-grained."
Development and evaluation of an ontology for guiding appropriate antibiotic prescribing (Bright et al., 2012)	Inappropriate antibiotic prescribing/ Antimicrobial resistance	To develop and apply formal ontology creation methods to the domain of antimicrobial prescribing and to formally evaluate the resulting ontology through intrinsic and extrinsic evaluation studies	Using Ontology, OWL, SWRL	Facilitate the creation and sharing of application-independent CDS modules/ Evidence of the potential usefulness of ontology for both knowledge maintenance and alter generation	Limited generalizability of the evaluation findings/ Evaluations occurred in a laboratory setting. Thus perceptions of usefulness of the ontology to generate prescribing alerts might vary from date collected in clinic
SeDeLo: using semantics and description logics to support aided clinical diagnosis (Rodríguez-González et al., 2012)	Need for computer-aided decision support systems which could help experts and non-experts alike, in prescribing and understanding the given prescriptions or in diagnostic assistance	To develop a clinical diagnosis system by using SW technologies to infer diseases from symptoms, signs and laboratory tests formalized as logical descriptions	Description logics and semantic technologies	The ability to develop diagnosis decision support systems/ Efficient in clinical diagnosis	No scalable/ Need to improve the capacity of reasoning over ontologies/ Need to develop descriptions rules to improve the temporal efficiency of the system/ Need to apply to a wider range of illnesses

An RDF/OWL knowledge base for query answering and decision support in clinical pharmacogenetics (Samwald et al., 2013)	Handling the complex and large sets of data, definitions and clinical guidelines	Creating semantic knowledge base for clinical pharmacogenetics to address the issues	RDF/OWL	Increasing the likelihood of successful large-term maintenance and growth of the knowledge base	
Enhancing automated decision support across medical and oral health domains with semantic web technologies (T. Shah et al., 2014)	Heterogeneous data collection and storage formats, limited sharing of patient information and lack of decision support the shared information	To enable sharing of medical and oral health information of patients for medical and oral healthcare practitioners to query, discover and generate knowledge in health management systems	OWL ontology and SWRL rules	Effectiveness in reasoning/ Comprehensive cross-domain knowledge base/ Cross-domain communication	Monotonicity: new information does not change pre-existing information/ OWL does not support negation as failure and closed world assumption
Ontology-mediated distributed decision support for breast cancer (Dasmahapatra et al., 2005)	The varied nature of expertise is modeled by multiple ontologies that provide domain-specific grounding to concepts and relationships	Handling data and invoking services appropriate for the requirements of decision-making process	Domain ontologies for describing the relevant specialist information as indicated	The integration of heterogeneous types and formats of information sources for the purpose of retrieval / flexible open-end architecture	Use the framework in a limited clinical setting
Integrating healthcare knowledge artifacts for clinical decision support: Towards semantic web based healthcare knowledge morphing (Hussain & Abidi, 2009)	Demands on the systematic integration of knowledge from multiple sources, such as clinical guidelines, clinical pathways, knowledge of practitioners and so on	Synthesizing health knowledge through the semantic modeling of healthcare knowledge as ontologies and reasoning over the ontologies to derive a morphed knowledge object	Knowledge representation and annotation via ontologies/ Contextualizing ontologies/ Morphing constructs/ Morphing engine	Standardization of the domain-specific concepts and relations/ Specification of abstract knowledge	

Ontology-based modeling of clinical practice guidelines: a clinical decision support system for breast cancer follow-up interventions at primary care settings (Abidi et al., 2007)	Lack of an interaction environment	To develop an interactive Decision Support System (DSS) that enables family physicians to (a) access and utilize the said CPG at the point of care to provide standardized follow-up care; and (b) offer customized patient educational information targeting disease management, lifestyle behaviors, and psychological support.	Ontology creation	To reduce workload of specialists	
An architecture for the semantic enhancement of clinical decision support systems (Sanchez, Toro, Carrasco, Bueno et al., 2011)	Multidisciplinary, heterogeneous and disperse clinical information and decision criteria have to be handled by CDSS	Semantic enhancement of CDSS	Architecture with four layers: data layers, translation layer, ontology and reasoning layer, application layer	Reduplication of the knowledge base is lessened, and the resultant semantic layer is strengthened	Supporting experience based reasoning that will provide an experienced modelling and reuse on the production rules
Ontology Based System Architecture to Predict the Risk of Hypertension in Related Diseases (Sherimon et al., 2013)	Handling huge amount of datasets/ Representation of medical knowledge in a meaningful way for the computers to analyze and acquiring inferred data	To propose an ontology-based decision support system model/ To predict the risk of hypertension and diabetics in related diseases	Ontology creation	Differs sources can share and reuse the ontological concepts represented in a semantic way and thus integration of data is easier	

Integrating HL7 RIM and ontology for unified knowledge and data representation in clinical decision support systems (Zhang, Tian et al., 2016)	The difficulty in expressing domain knowledge and patient data in a unified formalism	To present a semantic-based approach to the unified representation of healthcare domain knowledge and patient data for practical clinical decision-making applications	Four phases of knowledge engineering cycle to develop a semantic healthcare knowledge base based on an HL7 reference information model	Use of ontology offers possibilities for knowledge reuse and sharing in a formal, explicit and consistent way	The gap between semantic healthcare knowledge base (SHKB) and existing knowledge representation models as well as patient information models for knowledge reuse and sharing

Appendix D

Questionnaire materials for ranking knowledge based on quality by health experts

This appendix presents materials that received ethical approval and were used for ranking knowledge based on quality by health experts. These were:

- Participant Information Sheet
- Knowledge ranking exercise
- Demographic Information Collection Form

D.1 Participants Information Sheet

TE WĀNANGA ARONUI O TĀMAKI MAKAU RAU

Date Information Sheet Produced:

06 Jan 2017
Project Title

A study to rank clinical knowledge in terms of quality for Clinical Decision Support System

An Invitation

Hello,

I am a PhD student at Auckland University of Technology (AUT), Auckland, New Zealand. I am working on using Semantic Web technology in Clinical Decision Support Systems (CDSSs) to extract and support high quality knowledge for decision making to conduct my PhD in Computer Science under supervision of Assoc. Prof. Dave Parry.

In order to identify high-quality knowledge for clinical decision support systems, some candidate knowledge quality metrics that are useful for knowledge and system performance have been collected in this study. To understand the importance of knowledge quality metrics, we asked some health experts to validate them by participating in an anonymous questionnaire. Now, This questionnaire is based on ranking potential knowledge in terms of quality.

What is the purpose of this research?

The purpose of this research is to tank knowledge based on quality among set of extracted knowledge for specific concept (E.g. here the knowledge is related to the "Tuberculosis Arthritis") for Clinical Decision Support System as part of my research in PhD of Computer Sciences. The results will be published and presented in academic publications/presentations.

How was I identified and why am I being invited to participate in this research?

You are invited as someone interested in health informatics. Those who have knowledge about clinical decision making are particularly welcome. This questionnaire is anonymous and there is no need to write your contact details.

What will happen in this research?

Decision making is an essential activity for clinicians in the healthcare domain. Experts play an important role in decision making. However, experts may make a wrong decision, or not be available to make the decision. To this end, informatics researchers have proposed many methods to extract clinical knowledge using computers for the purpose of decision making. A well-known approach in this field is Clinical Decision Support System (CDSS). The CDSS improves the level of decision making. The knowledge used in the CDSS must be both up to date and appropriate for the cases that are being presented to it. Obviously, inappropriate knowledge can have negative influence on decision making. Finding the latest accurate clinical knowledge is difficult since knowledge is changing rapidly and it might be proposed by different organizations in different formats. To the best of our knowledge, the quality of knowledge using in CDSSs has only been considered to a minor extent. This study aims to propose a model for assessing the quality of extracted knowledge to support better decisions. This questionnaire aims to ask health experts (i.e. health informatics scholars and practitioners) to rank knowledge based on quality among the proposed knowledge.

What are the benefits?

The potential benefit of this research is to allow me to complete my PhD and potentially enhance the human decision making by using semi-automatic knowledge quality assessment mechanism.

How will my privacy be protected?

The questionnaire is anonymous and you will not be identified.

How do I agree to participate in this research?

You will not need to complete a consent form. You can agree to participate by completing questionnaire in an online questionnaire in a public URL.

Will I receive feedback on the results of this research?

Yes, Results will be put in a public URL and published via a Health Informatics conference/journal.

You may also contact me or my supervisor at a later date, using the details below, for a summary of findings.

What do I do if I have concerns about this research?

You are under no obligation to accept this invitation. If you decide to participate you have the right to:

- Decline to participate
- Ask any question of myself or my supervisor about the study at any time during participation.

Any concerns regarding the nature of this project should be notified in the first instance to the Project Supervisor, Assoc. Prof. Dave Parry, dparry@aut.ac.nz, +6499219999 xtn 8918.

Concerns regarding the conduct of the research should be notified to the Executive Secretary of AUTEC, Kate O'Connor, ethics@aut.ac.nz , 921 9999 ext 6038.

Whom do I contact for further information about this research?

Researcher Contact Details:
Seyedjamal Zolhavarieh
PhD Candidate
School of Computer Science
Auckland University of Technology (AUT)
Auckland 1142, New Zealand
Mob: +64210474720

szolhava@aut.ac.nz

Project Supervisor Contact Details:
Assoc. Prof. Dave Parry
School of Computer Sciences
Auckland University of Technology (AUT)
Auckland 1142, New Zealand
+6499219999 xtn 8918
Fax 649921 9944

dparry@aut.ac.nz

Approved by the Auckland University of Technology Ethics Committee on 25 September 2015, AUTEC Reference number 15/350.

D.2 Knowledge ranking exercise

Knowledge ranking exercise

By doing this questionnaire you indicate your consent to participate. These questions are about clinical knowledge extracted from PubMed search engine that are used for decision making and Clinical Decision Support Systems (CDSSs). Please rank the following knowledge based on age, citation, relevancy and accuracy. For your information:

Age of knowledge: indicates how old the knowledge is. It is used to rank knowledge based on newest to the oldest one as our system is looking for the new and updated knowledge.

Citation of knowledge: illustrates the number of citing, referring, and quoting knowledge used for different purposes. It is used to rank knowledge based on the knowledge with large number of citations to the knowledge with small number of citations.

Relevancy of knowledge: shows the knowledge contains relevant information to support the user query.

Accuracy of knowledge: shows how accurate the knowledge is.

Note: all of the knowledge are extracted from PubMed search engine via a query for "Tuberculosis Arthritis" using best match option with Title/Abstract and English language filters. After applying the query in PubMed search engine we receive this set of knowledge. Please help us to rank the high quality knowledge among these extracted knowledge for the purpose of clinical decision making.
Assumption: We assume that the abstracts explain correctly the nature of knowledge and show the information included in the body of knowledge.

Knowledge item 1: Tuberculosis arthritis of the metatarsal phalangeal: a rare location.

Citation : Berrady, M. A., Hmouri, I., Benabdesslam, A., Berrada, M. S., & El Yaacoubi, M. (2014). Tuberculosis arthritis of the metatarsal phalangeal: a rare location. Pan African Medical Journal, 17(1).Chicago - Citation Number: 1
Date Created: 20/10/2014
Abstract: Tuberculosis TB is common in countries constituting endemic areas like Morocco, spinal sites represents half of osteoarticular locations, while peripheral locations in the limbs are rare. The authors relate in this observation the case of a particular location of tuberculosis arthritis. It is osteoarthritis of themetatarsophalangeal joint of the 2(nd) ray of the foot. Clinical signs were characterized by a moderately painful swelling of the dorsum of the foot with slow evolution. The definitive diagnosis was histologically obtained. Clinical cure was achieved after 09 months of medical treatment.

1. K1

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 2: Periprosthetic tuberculosis of the knee joint treated with anti-tuberculosis drugs: a case report.

Citation : Tekin, K. S., Sipahioğlu, S., & Calişir, C. (2012). Periprosthetic tuberculosis of the knee joint treated with antituberculosis drugs: a case report. Acta orthopaedica et traumatologica turcica, 47(6), 440443. Chicago - Citation Number: 2

Date Created: 10/02/2014

Abstract: We report a 55year old man with periprosthetic tuberculosis infection following a total knee arthroplasty surgery performed during an active tuberculosis infection. The patient was conservatively treated with antituberculosis drugs and retention of prosthesis. There was no recurrence during an 18month followup period. Tuberculosis arthritis should be considered in the differential diagnosis in patients with osteoarthritis requiring replacement surgery. Conservative treatment with antituberculosis drugs may be an option in periprosthetic tuberculosis infections without loosening.

2. K2

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 3: Tuberculosis arthritis and tenosynovitis.

Citation: Pattamapaspong, N., Muttarak, M., & Sivasomboon, C. (2011, November). Tuberculosis arthritis and tenosynovitis. In Seminars in musculoskeletal radiology (Vol. 15, No. 05, pp. 459469). © Thieme Medical Publishers. Chicago - Citation Number: 11

Date Created: 14/11/2011

Abstract: The incidence of extrapulmonary tuberculosis (TB) has been rising due to theincreasing number of immunosuppressed patients. Musculoskeletal system accounts for 25% of extrapulmonary TB. Most of the musculoskeletal TB involves the spine. TB of peripheral joints and tendons occur infrequently, but if untreated, it can cause serious joint and tendon destruction as well as spread of the infection to the surrounding bursa, muscle, and other soft tissues. The diagnosis of TB of joints and tendons is difficult due to the nonspecific clinical manifestations and imaging features. Concurrent active pulmonary TB is present in <50% of the patients. A positive chest radiographic finding or a positive tuberculin test supports the diagnosis, but negative results do not exclude diagnosis. Although imaging features of TB of joints and tendons are nonspecific, certain findings such as relatively preserved joint space, juxtaarticular osteoporosis, cold abscesses, paraarticular soft tissue calcification, and rice bodies are suggestive of TB infection. Familiarity with these imaging features can help in making an early diagnosis and facilitating proper management.

3. K3

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 4: Pulmonary tuberculosis and tuberculous arthritis of knee joint associated with rheumatoid arthritis treated with antitumor necrosis factor (TNF)alpha medication: a case report.

Citation: Nalbant, S., Özyurt, M., Yıldırım, M., & Kuskucu, M. (2012). Pulmonary tuberculosis and tuberculous arthritis of knee joint associated with rheumatoid arthritis treated with antitumor necrosis factor (TNF)alpha medication: a case report. Rheumatology international, 32(9), 28632866. Chicago - Citation Number: 7

Date Created: 29/08/2012

Abstract: Tuberculosis infection (TB) is one of the most important problems for the rheumatoid arthritis (RA) patients treated with antiTNF agents. Pulmonary tuberculosis is the most common clinic form of the TB in these patients. However, tuberculosis arthritis is very rare. We present here a 72yearold Caucasian woman with seropositive RA, treated with etanercept/adalimumab for the last 2 years, who presented with resistant knee pain and joint effusion. We believe that this treatment caused the tuberculosis in this patient, which is the most worried complication. Interestingly, tuberculosis was in the knee joint at this time.

4. K4

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 5: Leuconostoc bacteremia in a patient with amyloidosis secondary to rheumatoid arthritis and tuberculosis arthritis.

Citation: Shin, J., Her, M., Moon, C., Kim, D., Lee, S., & Jung, S. (2011). Leuconostoc bacteremia in a patient with amyloidosis secondary to rheumatoid arthritis and tuberculosis arthritis. Modern rheumatology, 21(6), 691695. Chicago - Citation Number: 7

Date Created: 14/12/2011

Abstract: Leuconostoc infections are rare and usually occur in immunocompromised patients. This report describes a case of Leuconostoc lactis bacteremia in a patient with coexisting rheumatoid arthritis and tuberculosis arthritis. A disrupted gastrointestinal barrier due to gastrointestinal amyloidosis in longstanding rheumatoid arthritis and tuberculosis arthritis could be a risk factor for Leuconostoc bacteremia. Despite aggressive antibiotic treatment, the patient progressed to septic shock and multiorgan failure. The fatal course might have been caused by rapid progression of gastrointestinal pathology, which could be a risk factor for Leuconostoc bacteremia.

5. K5

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

knowledge item 6: Tuberculosis in children with congenital immunodeficiency syndromes.

Citation: Doğru, D., Kiper, N., Özçelik, U., Yalçin, E., & Tezcan, I. (2010). Tuberculosis in children with congenital immunodeficiency syndromes. Tuberkuloz ve Toraks, 58(1), 5963. Chicago - Citation Number: 9

Date Created: 02/06/2010

Abstract: Patients with congenital immunodeficiency (CID) syndromes are susceptible to various microorganisms. However, relatively few CID disorders develop mycobacterial disease. We describe clinical features, laboratory findings and therapeutic outcome of children with CID who had tuberculosis disease. Medical reports of 10 patients were reviewed. Three patients had chronic granulomatous disease, two had common variable immuno deficiency, the others had cyclic neutropenia, combined immunodeficiency, hyperimmunoglobulin E syndrome, selective IgA deficiency and Xlinked agammaglobulinemia. Eight patients presented with pulmonary tuberculosis, one had tuberculosis arthritis, one had tuberculosis osteomyelitis. There was acid fast bacilli in sputum of two, bone marrow aspiration in one and postmortem lung biopsy specimen in one patient. Mycobacterium tuberculosis grew in sputum of one and articular fluid aspirate of one patient. One patient was diagnosed with bone biopsy specimens characteristic for tuberculosis. The remaining three patients were diagnosed to have tuberculosis disease as they had positive tuberculin skin test and clinical and radiologic findings unresponsive to nonspecific treatment. All patients were treated with antituberculous drugs. Mycobacterium species may be important pathogens in children with CID, especially in endemic regions.

6. K6

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 7: Posttraumatic chylous knee effusion.

Citation: Tahara, M., Katsumi, A., Akazawa, T., Otsuka, Y., & Kitahara, S. (2011). Posttraumatic chylous knee effusion. The Knee, 18(2), 133135. - Citation Number: 3

Date Created: 07/02/2011

Abstract: Chylous joint effusion is a rare condition in which synovial fluids containing large amounts of lipids take on a milky appearance as a result. We report on a 19yearold male patient with posttraumatic chylous knee effusion. Several days after striking his knee against the ground because of a traffic accident, his left knee showed obvious swelling. Aspiration of his knee was performed, yielding 70ml of purulentappearing fluid. To distinguish this condition from purulent or tuberculosis arthritis, arthroscopic biopsy and debridement were performed. Arthroscopic examination visualized distinctive yellowwhite soft lesions covering much of the joint capsule, resembling a cobweb. Tissue cultures for bacteria were negative. Pathologically, we identified clusters of xanthoma cells with fibrin exudation due to disruption of the synovium and intraarticular fat pad necrosis. Centrifuging the aspiration fluid yielded a thick creamy lipid layer as the supernatant. A fresh drop preparation showed that the specimen contained innumerable fat globules, which stained red with oil red O stain. The patient was able to walk without difficulty or further swelling of his knee at the end of the second postoperative week. Posttraumatic chylous effusion is selflimited. Purulent arthritis or tuberculosis arthritis, however, should still be the presumptive diagnosis in such cases. Arthroscopic irrigation and debridement should be considered for these traumatic cases to confirm diagnosis and to speed up recovery.

7. K7

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 8: Cementless total hip arthroplasty for the management of tuberculosis coxitis.

Citation: Ozturkmen, Y., Karamehmetoglu, M., Leblebici, C., Gokçe, A., & Caniklioglu, M. (2010). Cementless total hip arthroplasty for the management of tuberculosis coxitis. Archives of orthopaedic and trauma surgery, 130(2), 197203. - Citation Number: 23

Date Created: 29/12/2009

Abstract:

INTRODUCTION: Tuberculosis arthritis of the hip is a crippling disease and there is need for an effective and acceptable treatment for the hips with bone destruction. The aim of this report was to evaluate the efficacy of the diagnostic method for hip tuberculosis and clinical results of the patients to clarify the question of whether a total hip arthroplasty (THA) should be attempted on a patient with a current or previous infection.

MATERIALS AND METHODS: Nine patients with active tuberculosis of the hip, treated by cementless THA, were analyzed retrospectively. The mean age of the patients at diagnosis was 43.4 years (range 2272 years). Laboratory tests of all the patients revealed high erthrocyte sedimentation rates (ESR) and Creactive proteins. Plain radiographs showed bone destruction with joint space narrowing in all patients. Magnetic resonance imaging (MRI) scans showed fluid within the joint in five patients. Two patients had associated pulmonary tuberculosis. To confirm the clinicoradiological diagnosis, an open biopsy was performed for histopathological examinations of all the hips. Tuberculosis of the hips was treated with primary cementless THA, followed by postoperative antituberculous medication for 1 year. The inflamed soft tissues and the destroyed bones were completely resected and curetted out at the time of operation.

RESULTS: At the final evaluation, the mean Harris Hip Score improved to 94.8 (range 9098 P = 0.003). ESR became normal, less than 15 mm/h, with a mean time of 4 months (range 29 months). The Creactive protein was normal, less than 0.8 mg/dl, after a mean time of 3 months (range 17 months). With an average followup of 5.6 years (range 28 years), no reactivation of tuberculosis infection was found in each patient. All of the femoral stems and acetabular cups were radiologically stable and demonstrated signs of bone ingrowth at the final followup. All histopathologic examinations showed granulomatous lesions including epitheloid histiocytes surrounded by lymphocytes.

CONCLUSIONS: Cementless THA can be safely performed in advanced tuberculosis of the hip for providing symptomatic relief and functional improvement of the hips. Complete curettage and resection of the infected tissue and postoperative antituberculous chemotherapy with a minimum of 1year duration are very important in preventing reactivations.

8. K8

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 9: Reactivation of ancient joint tuberculosis of the knee following total knee arthroplasty after 61 years: a case report.

Citation: De Haan, J., Vreeling, A. W. J., & Van Hellemondt, G. G. (2008). Reactivation of ancient joint tuberculosis of the knee following total knee arthroplasty after 61 years: a case report. The Knee, 15(4), 336338. - Citation Number: 24

Date Created: 27/06/2008

Abstract: The prevalence of pulmonary tuberculosis is increasing and is associated with a rise in skeletal tuberculosis. Even after appropriate antituberculosis therapy, reactivation of the infection may occur, even after many years. In this case report we describe a patient who had a reactivation of tuberculosis in the knee after total knee arthroplasty. At the age of 14 years, the patient had isolated tuberculosis arthritis of the left knee. Reactivation occurred after total knee arthroplasty 61 years later, at the age of 75. The patient was treated with a combined therapy. first the joint was irrigated with povidineiodine and saline solution, and gentamicin beads were left behind. When the cultures revealed Mycobacterium tuberculosis, drug therapy of isoniazid, rifampicin, ethambutol and pyrazinamide was started and was continued for 9 months postoperatively. At a recent followup, the patient is doing well, with good range of motion in the knee.

9. K9

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 10: Tuberculosis arthritis: A review of 27 cases.

Citation: AlSaleh, S., AlArfaj, A., Naddaf, H., Haddad, Q., & Memish, Z. (1998). Tuberculous arthritis: a review of 27 cases.

Annals of Saudi medicine, 18(4), 368369. - Citation Number: 23

Date Created: 08/03/2007

Abstract: No abstract

10. K10

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 11: Septic arthritis in patients with human immunodeficiency virus.

Citation: Zalavras, C. G., Dellamaggiora, R., Patzakis, M. J., Bava, E., & Holtom, P. D. (2006). Septic arthritis in patients with human immunodeficiency virus. Clinical orthopaedics and related research, 451, 4649. Chicago - Citation Number: 29

Date Created: 13/10/2006

Abstract: The literature contains few descriptions of the infective organisms and diagnostic issues associated with musculoskeletal infections in patients with HIV. We retrospectively reviewed 19 patients with HIV treated at our musculoskeletal infection ward for septic arthritis. The mean CD4 count was 154/mm (range, 7482/ mm), and 11 patients had a CD4 count < 200/mm and were diagnosed with AIDS. The most common pathogen (six patients) was oxacillinresistant Staphylococcus aureus. Mycobacterial infections occurred in three patients but no fungal pathogens were identified. Septic arthritis was monoarticular in 14 patients and involved the knee in eight patients, the hip in three patients, and the wrist in three patients. Five patients presented with polyarticular septic arthritis. All mycobacterial infections and four of the five polyarticular infections occurred in patients with a CD4 count < 200/mm. Patients with CD4 count < 200/mm had a lower joint fluid WBC count compared to patients with a CD4 count > 200/mm (40,500 vs 69,000/mm). Oxacillinresistant Staphylococcus aureus was the most common pathogen. A high index of suspicion for Mycobacterium. tuberculosis arthritis and polyarticular septic arthritis is necessary in patients with HIV and a CD4 count < 200/mm.

11. K11

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 12 : Advanced imaging of tuberculosis arthritis.

Citation: Moore, S. L., & Rafii, M. (2003). Advanced imaging of tuberculosis arthritis. In Seminars in musculoskeletal radiology (Vol. 7, No. 02, pp. 143154). Copyright© 2002 by Thieme Medical Publishers, Inc., 333 Seventh Avenue, New York, NY 10001, USA. Tel.:+ 1 (212) 5844662. - Citation Number: 12

Date Created: 15/08/2003

Abstract: Musculoskeletal manifestations are seen in approximately 3% of tuberculosis (MTb) cases, more commonly in the spine. Extraaxial bone and joint MTb is infrequently encountered in the West. In the last decade, public health strategies for control of MTb have been so successful in industrialized countries that many clinicians are unfamiliar with the range of extrapulmonary manifestations of MTb and therefore hold a low index of suspicion for MTb in the diagnosis of bone and joint infection. MTb, however, persists as a serious and significant cause of musculoskeletal pathology in many parts of the world and for specific patient cohorts in industrialized countries. Knowledge of the patient groups at risk and awareness of the varied osteoarticular manifestations of MTb are essential for timely diagnosis and intervention and potential cure.

12. K12

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 13: Multifocal tuberculosis presenting with osteoarticular and breast involvement.

Citation: Bodur, H., Erbay, A., Bodur, H., Yilmaz, O., & Kulacoglu, S. (2003). Multifocal tuberculosis presenting with osteoarticular and breast involvement. Annals of clinical microbiology and antimicrobials, 2(1), 6. - Citation Number: 18

Date Created: 24/03/2005

Abstract:

BACKGROUND:Polyarticular involvement, wrist and ankle arthritis are uncommon presentation of skeletal tuberculosis. Tuberculosis of the breast is also extremely rare.

CASE PRESENTATION:Wrist, ankle and breast involvement were detected in the same patient. Mycobacterium tuberculosis was isolated from both synovial and breast biopsy specimen cultures.

CONCLUSIONS:In general, tuberculosis arthritis is a frequently missed diagnosis, especially in different clinical patterns. A high level of suspicion is required particularly in highrisk populations and endemic areas.

13. K13

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 14: Concurrent gout and Mycobacterium tuberculosis arthritis.

Citation: Lorenzo, J. P., Csuka, M. E., Derfus, B. A., Gotoff, R. A., & McCarthy, G. M. (1997). Concurrent gout and Mycobacterium tuberculosis arthritis. The Journal of rheumatology, 24(1), 184186. - Citation Number: 19

Date Created: 26/03/1997

Abstract: Concurrent joint infection with Mycobacterium tuberculosis (TB) and demonstration of intraarticular monosodium urate (MSU) crystals has not previously been reported. We describe a patient with chronic tophaceous gout from whose joints both TB and MSU crystals were isolated. We propose a mechanism to explain this condition.

14. K14

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 15: Tuberculous arthritis of the kneean unusual presentation.

Citation: Chhabra, S., Garde, A., & Singh, H. (1995). Tuberculous arthritis of the kneean unusual presentation. Journal of postgraduate medicine, 41(4), 110. - Citation Number: 3

Date Created: 04/04/2000

Abstract: A 54 year old male who had an unusual clinical manifestation and radiological features proven to have tuberculosis arthritis of the knee on synovial biopsy is presented here.

15. K15

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 16: Acute arthritis and human immunodeficiency virus infection in Rwanda.

Citation: Blanche, P., Taelman, H., Saraux, A., Bogaerts, J., Clerinx, J., Batungwanayo, J., ... & Van de Perre, P. (1993). Acute arthritis and human immunodeficiency virus infection in Rwanda. The Journal of rheumatology, 20(12), 21232127. - Citation Number: 32

Date Created: 26/07/1994

Abstract:

OBJECTIVE: To determine the etiology of acute arthritis observed in adults and to define its relationship with human immunodeficiency virus 1 (HIV1) infection in Kigali, capital city of Rwanda.

METHODS: From September 1, 1989 until March 31, 1990 we conducted a study of all new patients admitted with acute arthritis to the outpatient and inpatient services of the Department of Internal Medicine at the Centre Hospitalier de Kigali, in Kigali, Rwanda, a city highly endemic for HIV infection.

RESULTS: Thirtysix patients (27 men 9 women, mean age: 31 years, range 1865) were included in the study. Twentysix (72%) were HIV seropositive. Two main diagnostic categories emerged, both strongly associated with HIV infection: (1) aseptic arthritis: 16 (44.5%) patients including 12 (33.5%) patients with spondyloarthropathy of whom 10 (83%) were HIV seropositive, and 4 (11%) patients with HIV related arthritis, (2) septic arthritis: 11 (30%) patients of whom 9 (82%) were HIV seropositive, including 4 with gonococcal, 2 with staphylococcal, 1 with Salmonella B and 2 with tuberculous arthritis.

CONCLUSION: In an area highly endemic for HIV, acute arthritis should be considered a possible manifestation of HIV infection and should prompt HIV testing. [PIP] HIV infection is highly endemic in Kigali, Rwanda. The authors report findings from a study conducted from September 1, 1989 to March 31, 1990, to determine the etiology of acute arthritis observed in adults and its relationship with HIV1 infection in the city. Careful medical histories and full clinical evaluations were conducted upon each new patient admitted with acute arthritis to the outpatient and inpatient services of the Department of Internal Medicine at the Centre Hospitalier de Kigali over the period. 27 men and 9 women of mean age 31 years in a range of 1865 years presented, of whom 72% were HIV seropositive. Aseptic arthritis was diagnosed in 16 patients of whom 14 were HIV seropositive. 12 patients fulfilled the criteria of spondylarthropathy of whom 10 were HIV seropositive. There were 4 cases of HIVrelated polyarthritis, while septic arthritis was identified in 11 patients of whom 9 were HIV seropositive, including 4 with gonococcal, 2 with staphylococcal, 1 with Salmonella B, and 2 with tuberculosis arthritis. The authors stress on the basis of these findings the need in an area highly endemic for HIV to consider acute arthritis a possible manifestation of HIV infection which necessitates the testing for HIV.

16. K16

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 17: Arthroplasty in tuberculosis of the knee. Two cases of missed diagnosis.

Citation: Wray, C. C., & Roy, S. (1987). Arthroplasty in tuberculosis of the knee: Two cases of missed diagnos. Acta Orthopaedica Scandinavica, 58(3), 296298. Chicago - Citation Number: 22

Date Created: 20/10/1987

Abstract: Active tuberculosis arthritis was diagnosed in two patients after they had undergone total knee replacement. Antituberculous therapy was successful.

17. K17

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

Knowledge item 18: Shortcourse chemotherapy for tuberculosis in children.

Citation: Abernathy, R. S., Dutt, A. K., Stead, W. W., & Moers, D. J. (1983). Shortcourse chemotherapy for tuberculosis in children. Pediatrics, 72(6), 801806. - Citation Number: 73

Date Created: 07/01/1984

Abstract: Shortcourse, largely twiceweekly chemotherapy for tuberculosis was introduced in the United States for treatment of adults with pulmonary disease by the Arkansas State Department of Health in 1976. Since 1977, 50 children with tuberculosis have been treated with rifampin, 10 to 20 mg/kg, and isoniazid, 10 to 20 mg/kg daily for one month followed by 10 to 20 mg/kg of rifampin and 20 to 40 mg/kg of isoniazid twice a week for another 8 months. Ages ranged from 4 months to 15 years with a median age of 3 years. A presumptive diagnosis of tuberculosis was made on the basis of 10 mm or more of induration to 5 TU of purified protein derivative and a chest film or other findings compatible with tuberculosis. Three children had extrapulmonary disease (two had cervical adenitis, one had tuberculosis arthritis). Of the 47 children with pulmonary disease, 32 were asymptomatic. The results were excellent. Symptoms cleared in 1 to 2 months. Most pulmonary infiltrates had cleared by 10 months, but hilar adenopathy rarely cleared in less than 2 years. Drug toxicity occurred in only one patient (vomiting of rifampin). This treatment appears to be safe, effective, inexpensive, short and simple enough to ensure cooperation or to allow personnel to administer drugs directly to children from socially disorganized families.

18. K18

	YES	NO
Is the knowledge relevant?		
Is the knowledge accurate?		

19. Please rank the knowledge items in this set in terms of quality of knowledge (by considering all knowledge QMs: Age, Citation, Relevancy, and Accuracy)?

20. Which knowledge item has highest quality ? Please explain briefly what is your criteria to choose this knowledge as the most qualified knowledge ?

21. Please rank the knowledge items in this set in terms of Age of knowledge ?

22. Please rank the knowledge items in this set in terms of Citation of knowledge ?

23. Please rank the knowledge items in this set in terms of Relevancy of knowledge ?

24.Please rank the knowledge items in this set in terms of Accuracy of knowledge ?

25. What other criteria would you use for assessing knowledge quality ?

D.3 Demographic Information Collection Form

Please circle the age bracket that you belong to:

- 20-29
- 30-39
- 40-49
- 50-59
- 60-69

How many years you are in practice ?
How confident are you in using Clinical Decision Support System? (Please select one)

conteExtremely confident 10 9 8 7 6 5 4 3 2 1 not at all confidentnt...

How much you think computer-based systems can be useful in human decision making? (Please tick one)

- Extremely useful
- Quite useful
- Moderately useful
- Slightly useful
- Not at all useful

Approved by the Auckland University of Technology Ethics Committee on 25 September 2015, AUTEC Reference number 15/350.