A New Trend for Knowledge Based Decision Support Systems Design

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Abstract
Knowledge-Based Decision Support Systems (KBDSS) have evolved greatly over the last few decades. The key technologies underpinning the development of KBDSS can be classified into three categories: technologies for knowledge modelling and representation, technologies for reasoning and inference, and Web-based technologies. In the meantime, service systems have emerged and become increasingly important to value adding activities in the current knowledge economy. This paper provides a review on the recent advances in the three types of technologies, as well as the main application domains of KBDSS as service systems. Based on the examination of literature, future research directions are recommended for the development of KBDSS in general and in particular to support decision making in service industry.

Keywords: DSS, KBDSS, Intelligent DSS, knowledge modelling and representation, reasoning and inference, application domains, service systems

1. Introduction

Decision support Systems (DSS) are developed to support decision makers in their semi-structured tasks and appeared towards the end of 60's (Ackoff, 1968). The first architecture proposed by (Sprague and Carlsson, 1982) was composed by: 1. A model base management system; 2. A data base management system; 3. A human-computer interface.

In order to develop systems the most usable possible, in the 1990s, DSSs were enriched by techniques rooted in Artificial Intelligence, particularly the introduction of a knowledge base into the architecture previously described, so as to give the system the capacity for reasoning. This approach is an Expert Systems type approach, for which the modes of reasoning and the problem to be solved are modelled first and then used on a machine by way of inference engines. This approach leads to develop Intelligent DSS or also called Knowledge Based DSS.

According to (Marakas, 2003) the components of a DSS can usually be classified into five distinct parts:

- A database management system and the associated database: which stores, organizes, sorts and returns the data relevant for a particular context of decision making;
- A model base management system and the associated model base: which has a similar role to the database management system, except that it organizes, sorts and stores the organization's quantitative models;
- The inference engine and the knowledge base: which performs the tasks relating to recognition of problems and generation of final or intermediary solutions, along with functions relating to the management of the process of problem solving;
- A user interface: which is a key element in the functions of the overall system;
- A user: who forms an integral part of the process of problem solving.

Thus, in the architecture of these systems, we see the emergence of a technological part drawn from Artificial Intelligence, integrating knowledge modelling into the problem to be solved. The advantage to this architecture lies in the emphasis placed on reasoning in the taking of the decision, and supported by tools such as knowledge-based systems.

The purpose of this work is to study the evolution of Knowledge Based DSS (KBDSS) in recent years on several criteria. This paper is organized as follows. After this introduction, in a second part the used methodology is described and in the third section we draw a survey of technologies used for first knowledge modelling and second reasoning. In the fourth part, we present the main application domains for which KBDSS are successfully designed and we also detail which kind of technologies are used coming from the Web technologies. The fifth part is devoted to finding the relationships among the used technologies and the service application domains. These relationships are then used in order to present some recommendations for KBDSS design. In the last section the limitations of this work are identified and conclusions are drawn.

2. Methodology

We studied over 70 papers in order to define what the most used technologies are for knowledge modelling; technologies for reasoning as well as what are the principal application domains. In a previous study, Liu and Zaraté (2014) based their study on 29 studied papers and found two axis of Analysis: a. Knowledge Modelling Technologies and b. Reasoning Technologies. This study has been improved by analyzing many papers and a third axis of analysis (support service systems) is found. We noticed that in the last few years a new kind of technologies used for DSS design came from the IT field and more particularly the services system (Mora et al, 2014). This paper focusses on the analysis of technologies used for knowledge modelling as well as which kind of service systems used to design DSS as user friendly as much as possible. These used technologies for knowledge modelling constitute the criteria allowing the distinction from the reviewed papers.

The methodology used to select the papers includes four key steps: (1) An initial search was conducted with "ISI Web of Science". Keywords used for the initial search were "knowledge base", "reasoning", "Web-based", "decision support" and "service systems". We refined the search by selecting the Science Technology and Social Science in order to eliminate results from less relevant areas. The search is further refined by restricting to the period of 1990-2013. We believe that 1990 is an appropriate starting point for research in KBDSS (Kljajić, 2010). We used the "knowledge base", "reasoning", "Web-based", "decision support", and "service systems" because they have been used as keywords in most cited articles on the subject and to obtain the most complete results possible. (2) Then, on the basis of a thematic analysis of the abstracts of the selected papers, we eliminated those which did not address knowledge base or reasoning or Web-based technologies in relation to decision support and service systems. We also did a cursory reading of the articles that were eliminated to be sure that they were out of scope of our literature review. (3) We added a number of papers that were not included in ISI search results from three well-known journals in DSS area: International Journal of Decision Support Systems Technology, Journal of Decision Systems, and International Journal of Information and Decision Science. (4) We complemented our selection by adding three books widely cited in DSS field. The final selection includes 73 references as analysed in this literature review.

3. Survey on technologies

In order to analyze theses papers, we define several criteria. We firstly distinguish three criteria based on the used technologies, which are the used technology for knowledge modelling and then used technologies for reasoning implementation, and finally Web-based technologies.

3.1 Technologies for Knowledge Modelling

We firstly must distinguish the technologies used for knowledge modelling. We distinguish two kinds of knowledge representations**: clustering** and **ontology.** By knowledge we include all the **required facts for reasoning and producing results.**

The clustering techniques consist in dividing the knowledge in different classes or knowledge classification. Similar rules are represented in the same cluster and distinct clusters of rules are formed using representatives. Several papers use this kind of techniques (Armengol, 2010; Wakulicz-Deja et al., 2011; Yang et al., 2011Pombo et al., 2014; Ghrab et al., 2014). These authors assume that time is gaining when dealing with large knowledge base.

The ontology modelling technique consists in capturing consensual knowledge, i.e. not personal view of the target phenomenon but one accepted by a group; ontology is not just about presenting information to humans but also processing the information and reason about it. Some works have been conducted on ontology engineering process for which the following steps are proposed: feasibility study, kick-off, refinement, evaluation, maintenance. From the following authors (Cortes et al., 2001; Minutolo et al., 2012; Riano et al., 2012; Valls et al., 2010; Haghighi et al., 2013; Apostolou et al., 2011; Ouamani et al., 2014; Khare et al., 2012; Gil et al., 2012) several perspectives have been drawn along the two following axes: a. Clear understanding of how to build ontologies in a systematic way and b. Building fuzzy rules into ontology.

The two main knowledge representations consist in clustering and ontologies. Nevertheless, the considered knowledge can divide three kinds or levels: a. **contextual knowledge**; b. **content knowledge** and c. **unstructured knowledge**.

About contextual knowledge, (Montani, 2011) analysed context of knowledge which is seen through the DSS environment, such as clinical setting, knowledge states of the patients and physicians, and emotions; case-based reasoning suited for capturing contextual knowledge.

From the content knowledge we saw two sub-levels of knowledge: a. medical knowledge; b. organizational knowledge. For the medical knowledge, this kind of implementations have been studied in several works and medicine is the main application domain of KBDSS (for this point see section III.a.). In other hand (Valls et al., 2010) proposed a model of organizational knowledge in the K4Care project.

(Wang et al., 2011) proposed to develop a model for unstructured knowledge based on narratives documents for which Knowledge resided in client's records and stories. Some authors represent required knowledge for making decisions through Knowledge Editing systems or services (Colantonia et al., 2011). (Sun et al., 2013) use an Agent based approach in order to model Knowledge Decision Makers for ecosystem services. Some other authors propose to exploit this knowledge through data mining technics in order to elicit knowledge from explicit data sources (Cortes et al., 2001) or to discovery new knowledge (Armengol, 2010). In order to achieve this objective this paper presents several techniques of learning methods like for example on one hand lazy learning based on explanation-based learning and that does not cover all the space of known examples and on the other hand eager learning.

Modelling through technologies coming from Knowledge Management domain is always a good way to develop Knowledge Based DSS. (Timmons, 2013; Oduoza, 2010; Zielinski et al., 2014) use knowledge acquisition or capture, translation, and sharing approach; (Zimmermann et al., 2012) develop an approach based on knowledge capture from experience and lessons learnt; (Bousseba, 2014) develop a knowledge transfer methodology. (Johansson et al., 2010) propose a methodology for differentiate knowledge maturity during product-service systems projects in the Aerospace sector. Finally (Davi et al., 2014) develop a framework for knowledge management in the healthcare domain.

Another different way to model knowledge for decision making is to build a model of several indicators. This approach has been implemented through a DSS for information services by (Poppol et al., 1998). A different approach is developed for knowledge modelling thanks to networking by (Alkhuraiji et al., 2014). Independently of all these developed technics, it is also necessary to design methodologies for knowledge modelling. One methodology applied to quality management is proposed by (Pyon, 2009). All these modelling technologies are then used by inference engine in order to produce new piece of knowledge or solutions to a problem. We propose in the next section a classification of reasoning or inference technology based on the same 73 papers.

3.2 Technologies for Reasoning

We distinguish five reasoning or inference technologies: Rule-based reasoning (**RBR**), Case-based reasoning (**CBR**), Narrative-based reasoning (**NBR**), Ontology-based reasoning (**OBR**) Genetic Algorithms (**GA**), Optimization (**Opti**) and Simulation (**Simu**) technologies and finally Mining approaches (**Min**).

Several kind of rules modelling are used: Traditional RBR; Logical Elements Rule Method for assessing and formalizing clinical rules; Rule verification to ensure high quality of guidelines encoded in KB-DSS in the form of rules: redundancy, inconsistency, circularity, incompleteness. This technology is predominant and is used in the following systems implementation (Armengol, 2010;Cesario and Esposito, 2012;Huang et al., 2011; Kong et al., 2011; Medlock et al., 2011; Wakulicz-Deja et al., 2011Yang et al., 2011; Zhang, Lu and Zhang, 2011; Sampaio et al., 2014; Gu et al., 2012) . (Lee et al., 2012) propose a RBR inference approach based on Business Process Modelling. From these papers the following future directions of implementation are drawn to Belief RBR (vagueness, incompleteness, non-linear relationships) and fuzzy rule-based.

The Case-based reasoning technology relies on past and similar cases to find solutions to new problems; it is a king of implementation of a sort of automatic ranking of past lessons and making available best practice cases. Five steps are distinguished in the process of Case-based reasoning: interpretation, retrieval, reuse, revise, retain. The following authors have implemented KBDSS based on CBR (Cortes, 2001) (Bichindaritz, 2011) (Koo et al., 2014). The following trends are drawn for CBR: extensive application of ontologies to improve the use of the domain from past experiences and diminish impasse situations.

(Wang and Cheung, 2011) proposes a Narrative-based reasoning KBDSS. This system deals with unstructured narrative information. The objective is to share experience and lessons learned for decision making through stories and narratives. For this system an NBR algorithm comprises three key modules: key concept extraction, similarity analysis, and association analysis. For this implementation the author proposes as future work to measure the similarity among the key concepts in order to have a more precise determination on the similarity analysis and association analysis.

(Riano et al., 2012) and (Valls et al., 2010) propose to implement the reasoning technology for KBDSS through Ontology (Ontology-based technology). Knowledge is implemented through ontology navigation. The

K4Care project provides a Case Profile Ontology from a formal representation of all the healthcare concepts and relationships and constraints between concepts, related to the care of chronically ill patients. This project then implements a medical DSS reasoning loop. These authors precise that future ontology will include restrictions on the interactions among intervention plans with the purpose of extending the DSS with mechanisms to compare treatments.

(Huang, Pasquier and Quek, 2011) proposes a KBDSS based on Genetic algorithm. He implemented a co-evolutionary genetic algorithm for detecting gamma ray signals: 5 layer hierarchy – input layer, condition layer, rule layer, consequence layer, output layer are distinguished.

Independent of the used implementation technologies, KBDSS are developed for several kinds of application domains. Theses application domains are described in the following section. (Darmoul etl al, 2014) develop an artificial immune system to control disturbances in public transportation. Several authors use techniques from mining approach in order to support reasoning in KBDSS (**Min**). These mining techniques are developed by (Abidi, 2001; Liu et al., 2008).

Another point that must be mentioned is that some KBDSS are based on classical reasoning approach like for example Optimisation and Simulation technologies (**Opti** and **Simu**). (Devadasan et al., 2013; Cheung et al., 2005) use a multi-objective optimization approach respectively in the first study and a single objective optimization technic respectively in the second study in order elaborate collaborative planning. In the same application domain, network planning, coming from optimization studies, sensitive analysis is an interesting approach to develop indicators for medical diagnosis (Rodriguez-Gonzalez et al., 2013).

Nevertheless the design of KBDSS involves more technologies from new trends of Information and Communication like Web2.0, Web3.0 or Cloud Computing.

3.3 New Trends: Web based Technologies

As described by (Antunes et al., 2014) “Web1.0 is known as an early stage of the conceptual evolution of the World Wide Web, where users simply acted as publishers and consumers of content, as webpage information was closed to external editing. Rather than a specific technology update or specification, Web2.0 core was a transformation in the way web pages were made and used, adding a multitude of users responsible for all information management activities”.

At the same time in the Web2.0 the main improvement consists in the development of Collaborative Tools to support group activities like for example Decision Making Processes (Zaraté, 2013). Theses collaborative functionalities are generally implemented through Web Services.

The term Semantic Web (Berners-Lee et al., 2001), considered by many as an evolution of Web2.0 – hence the term, Web 3.0 (Lassila et al., 2007) means a set of technologies that includes ontologies, software agents and tules of logic. These technologies can greatly improve the ability to connect and automatically organize the content of information spread across multiple pages or sites (Kousetti et al., 2008). The mobility age arriving, a new evolution of the World Wilde Web consists in offering the possibility to users to access everywhere to their personal data, documents from everywhere. The personal data, documents are storage on servers usable from everywhere with any kind of devices. This new possibility is called Cloud Computing (Demirkan and Delen, 2013). We noticed that (De Meo et al., 2008) developed a DSS for electronic government based on Web Services. (Martinez-Garcia et al., 2013) propose a DSS in healthcare domain using Social Networks in the Web2.0 as in the same time (De Maio et al., 2011) publish a framework Knowledge based for supporting Decision Making in emergency situations using semantic web in the Web3.0. (Dixon et al., 2013; Demirkan et al., 2013) design two systems services oriented for which Knowledge is distributed on Cloud Application respectively in the healthcare domain and on a theoretical point of view. Finally (Delen et al., 2013) propose to develop DSS thanks to Data, Analytics as services implemented in the Web2.0, Web3.0 on a Cloud approach. The analysis conducted in this paper is based not only on the technologies used for knowledge modelling but also on the type of addressed application domains.

4. Survey on KBDSS Application in Service Systems

Based on the 73 papers reviewed, the application of the KBDSS in service systems can be classified into five main areas: healthcare service, public service, IT service, customer service and others. The applications in healthcare service are predominant.

4.1 KBDSS to support healthcare service

Given the potential value of KBDSS to support improvements in safety, quality, and efficiency, the adoption and use of KBDSS has become a global priority for healthcare service systems. The application of knowledge-based systems in healthcare started in early 1970s. Since then, KBDSS has been extensively explored to support decision making in all aspects of healthcare because of the fact that medical conditions are highly diverse, fast changing and sometimes unpredictable. This section presents the recent advancements of KBDSS in healthcare service decision making to support different tasks, including clinical, management (treatment) and follow-up, in particular,

- clinical diagnosis to improve the accuracy of analysis of conditions and adaption of evidence-based standard intervention plans to the conditions (Armengol, 2011; Medlock et al., 2011; Cesario and Esposito, 2012; Minutolo, Esposito and De Pietro, 2012; Riano et al., 2012; Schipper et al., 2012);
- clinical pathways to standardize medical activities and thereby improve healthcare quality (Yang et al., 2011) such as through the integration of workflow control into clinical guidelines (Lee et al., 2012);
- clinical risk assessment to help reduce medical errors and patient safety incidents and thus reduce the healthcare service costs caused by patient safety incidents (Kong et al., 2012);
- medication review to improve medication usage, leading to reductions in drug-related problems and potentially savings on healthcare system costs (Bindoff et al., 2012; Colantonio et al., 2012) and to evaluate the healthcare systems for the future policy development (Zielinski et al., 2014);
- preventive care using Cloud-based knowledge base with lessons learnt (Dixon et al., 2013);
- home care assistance to support the management of complex distributed healthcare systems (Valls et al., 2010);
- mental healthcare for offering timely and quality services so as to maintain the health of the community (Wang and Cheung, 2011);
- multimorbidity patients care supported by consensus decisions among a large number of healthcare professional (Martínez-García et al., 2013); and
- finally, it is worth noting that a guest editorial provides a good overview of KBDSS application to health sciences (Bichindaritz and Montani, 2011). More recently, Pombo et al. (2014) provided a systematic review on pain management using KBDSS to allow obtaining knowledge from clinical data produced by both healthcare professionals and patients.

4.2 KBDSS to support public service

A second main domain that knowledge-based service systems have been widely explored is public service, including e-government, transportation, education, and community safety. In recent years, e-government is a popular term adopted to indicate the use of ICT technologies for government agencies to improve both the range and quality of services to citizens, especially by enabling the interaction between citizens and government agencies. Today's e-government has become more complex and distributed than ever. KBDSS has played a key role in helping governmental decision makers to develop and activate new services that can tailor more citizens' needs and requirements by handling more government agencies and a great number of citizens simultaneously (De Meo et al., 2008). Furthermore, Apostolou et al. (2011) investigated the KBDSS contribution to e-government services in a continuously changing environment that may be caused by changing citizens' needs, legal regulations, availability of new technologies, outsourcing opportunities, and new service models. Another important public service area, transportation service, is sensitive to highly unpredictable disturbances from accidents, delays and traffic congestions etc., a prototype KBDSS has been developed to assist decision makers in performing disturbance management functions including the detection of disturbances, constructions of reaction strategies, supervised learning and memory of previous experiences with disturbances (Darmoul and Elkosantini, 2014). Focused on the case of South Korean expressway service, Koo et al. (2014) studied how KBDSS can help decision makers to evaluate the economic benefits when planning a new expressway. KBDSS has also found its way in the higher education service. For example, an ontology-based KBDSS which applies ontology learning processes from heterogeneous knowledge sources (ontologies, texts, and databases) has been developed to improve individual and collaborative learning through a process of periodic knowledge updating (Gil and Martin-Bautista, 2012; Ouamani et al., 2014). Public and community safety is certainly of great importance to public service which motivates KBDSS researchers to devote their attention to. Gu et al. (2012) explored a case-based KBDSS for safety evaluation decision making of thermal power plants. Last but not least, Timmons (2013) advocated for the importance of inclusive service including the social, cultural and economic needs of people with disability and their families. His work pays great attention to the role of knowledge translation in the decisions of construction of policy and service systems that are people-centered, taking into account the priorities and aspiration of individuals and emphasizing concepts of inclusion, choice and self-determination.

4.3 KBDSS to support IT service

The use of knowledge based systems has been proven to be a suitable approach to supporting decision making in IT service systems, such as information service and network services. Because of the broad boundary of information services, KBDSS has been well investigated over the years. An early research conducted by Poppol and Zenger (1998) examined the integration of knowledge base and measurement reasoning in the governance of nine information services across 152 companies. A key feature of KBDSS supported information services is not only in its large scale (across many companies) but also covering the whole lifecycle of IT projects, ranging from the early stage, for example the service system's architecture design, to the system's maintenance and evolution. Existing research seem to agree that it is important to capture and share knowledge represented by practical experience gained and lessons learnt. Zimmermann's work discussed the use of the combination of reference architecture, the meta-model, and the twelve modelling principles and practices for architectural knowledge management in IT services, addressing the extended scope of both presales design activities and architecture design on projects (Zimmermann et al., 2012). The knowledge mobilisation and network model proposed by Alkhuraiji et al. (2014) focused on the support for strategic intervention in IT project-oriented change management. In order to evaluate the IT service for network applications, a KBDSS using case-based reasoning has been built which not only has a knowledge base that captures network performance problems, applications characteristics and user profiles, it also has a case base that contains user's opinions (Sampaio et al., 2014). The study found that the service system is effective in improving its resilience to user's collusive and incoherent behaviours.

4.4 KBDSS to support customer service

In the service industry, customers are in the center of the service creation and delivery process. Because of the high importance of customer's presence for the value co-creation, customers have high visibility of the service quality and dependability, hence with low tolerance to poor service flexibility or service delay (Vargo et al., 2008; Jeon et al., 2011). Improving customer service naturally attracts many KBDSS researchers' interests, studying from service planning to quality control, from customer inquiry service to after-sale service. In the current e-service era, KBDSS using collaborative intelligence has proven effective in support finding the best collaborators during the formation and functioning stages of collaborative networks (Devadasan et al., 2013). Also from the network service planning perspective, Cheung's work addressed the issue of how to support changes in logistics services and shifting customer's demand based on a case study with DHL Hong Kong air-express courier service (Cheung et al., 2005). From a different point of view to address meeting customer demand fluctuation, an integrated approach is proposed for the simultaneous design of efficient managerial contracts and capacity planning for capital intensive service facilities (Jiang and Seidmann, 2014). Equally important, it is required to establish a structured framework that leads employees to make efforts to improve their service delivery processes and supports continuous improvement of service delivery processes based on the data about the process performance from a customer-perceived value-oriented viewpoint (Pyon et al., 2009). Making the right decision on customer service is a challenging task but crucial to businesses since customer service strongly influences the potential profitability of the companies. At early stages, KBDSS can help companies to properly respond to customer enquiries about product functions, deliver dates and sales price, so that finally the enquiries can be translated into customer orders (Oduoza, 2010). For later stage customer service, a KBDSS has been developed on the combination of association and ontology based text mining and has been applied to improve after-sale service for automotive domain (Khare and Chougule, 2012). In other domains such as aerospace industry where products have rather long lifecycles, product-service systems have been a hot topic for researchers. The concept of knowledge maturity is explored as a means to provide practical decision support, which increases decision makers' awareness of the knowledge base and supports cross-boundary discussions on the received maturity of available knowledge, thereby identifying and mitigating limitations (Johansson et al., 2010).

4.5 Others

Some other applications of knowledge-based service systems are scattered around various interesting domains, for example in detecting gamma ray signals in the universe (Huang, Pasquier and Quek, 2011), road safety with the application to car driving (Brezillon, Brezillon and Pomerol, 2009), consultancy service in multinational corporations context (Bousseba et al., 2014), land-use decision making under the influence of payments for ecosystem services (Sun and Müller, 2013), and waste water management (Cortes et al., 2001; Aulinas et al., 2011).

5. Relationships among application domains and used technologies

The previous sections looked at the used technologies in KBDSS and their application domains separately. This section presents the relationships between different technologies and that between the technologies and application domains. Recommendations on developing future KBDSS are subsequently provided.

5.1.Relationships

As discussed in section II, there are three main types of technologies in relation to KBDSS: technologies for knowledge modelling and representation, technologies for reasoning and inference, and the new trend in Web-based technologies. Main application domains of KBDSS are discussed in section III. The relationships among the technologies and applications are illustrated in Figure 1. As shown in the Figure, the four blocks in the relationship chart are technologies for knowledge modelling, technologies for reasoning and inference, Web-based technologies, and the application domains. Three types of relationships can be elicited. Type I relationships are the internal links between elements within the same block and represented by thin solid arrows. For example, links between clustering and ontology, as well as the links between different clinic diagnosis, treatment plan and follow up decisions (Yang et al., 2011). Type II relationship are external links between different blocks, such as links between modelling and reasoning technologies. These types of relationships are represented by solid block arrows. For a KBDSS to properly function in any domain areas, it has to be created using appropriate both knowledge modelling and reasoning technologies (Riano et al., 2012; Valls et al., 2010). Type III relationships are cross links among elements in different blocks which are represented by dashed thin lines. For example, the links from ontology technology through ontology-based reasoning to healthcare application domain demonstrate that specific knowledge representation technology such as ontology needs particular reasoning mechanism and fits particularly well in medical application, because of the nature of medical decision situation with high variety, high dynamics and unpredictability (Riano et al., 2012). Understanding the different types of relationships within, between and across different blocks will help us to justify and choose the right technologies for the development of knowledge base and reasoning mechanisms for the right application domain.

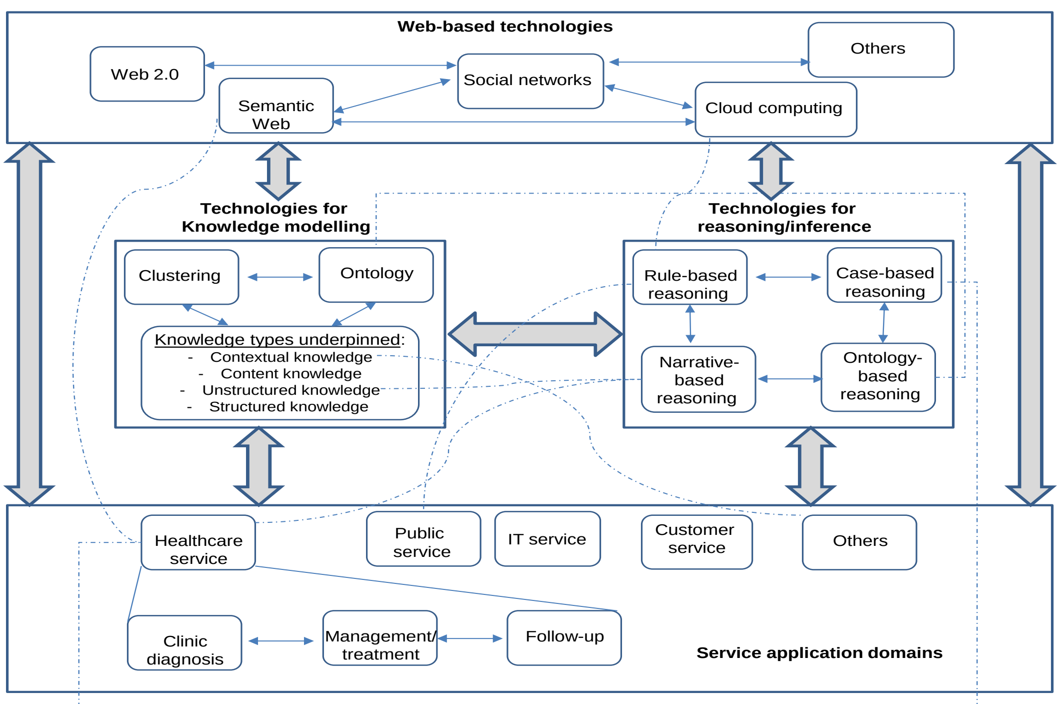

Figure 1 Three types of relationships among technologies and applications

The details of the above external links (i.e. Type II and Type III) are summarized and further elaborated more clearly in Figure 2. For clarify purpose, this Figure does not include internal links (i.e. Type I links). In this Figure 2, a star sign represents an explicit link found between two types of technologies (knowledge modelling and reasoning), as well as with application domains (Healthcare, public services, IT services and customer services) in the literature. If the KBDSS is built upon the third type of technologies, i.e. Web-based technologies (such as Web 2.0, semantic web, cloud computing or social networks), then the star sign is surrounded by a globe in the representation. As can be seen from the Figure 2, the stars concentrate in some specific areas but are scarce in other areas. The following observations have been made. Firstly, in terms of knowledge reasoning, RBR (rule-based reasoning) seems to have connections to all knowledge modelling technologies and application domains, followed by CBR (case-based reasoning) slightly behind. GA is the least used (only has a link to customer service domain) based on the literature included in this review paper. Secondly, in terms of knowledge modelling technologies, both clustering knowledge and ontology technology have strong links to most of the service application domains. The last observation is that majority of the links are Web-based, which means that currently service systems have already taken advantage of the technologies to improve service mobility and flexibility, especially Web technology-based service systems can provide unprecedented convenience to users, either general public or business customers (Keenan, 2013).

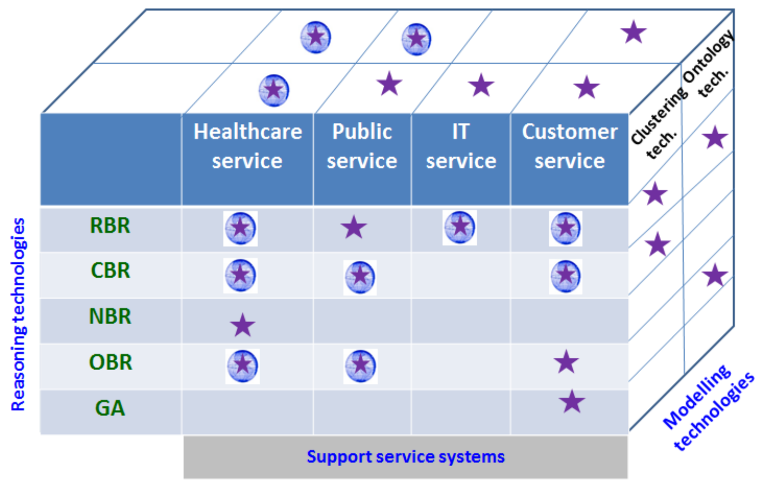

Figure 2 Elaboration on links between technologies and service application domains

5.2. Recommendations

Based on the examination of the KBDSS technologies and application domains, certain challenges and trends have been observed for future research directions from two perspectives: KBDSS development in general and in particular to support service decision making.

<u>Challenges and recommendations for future KBDSS development in general:</u>

- Even though ontologies have been well researched as a means of capturing knowledge and modelling knowledge structure, building a moderately sized ontology in a KBDSS is still a time consuming task. One challenge lies in the acquisition of domain-specific terminology and relationships from a conceptual model. To meet the challenge, ontology learning is emerging to discover ontological knowledge from various forms of data automatically or semi-automatically (Easton, Davis and Roberts, 2011). Key elements of ontology learning include information extraction, ontology discovery and ontology organization. It is hoped that the advancement of relevant technologies such as cluster analysis may shed lights on identifying the relationships between terms applicable to the domain knowledge. Ontology learning is certainly in its infancy and requires more research in the future in order to support the creation of better KBDSS as service systems.
- Even individual reasoning technology such as rule-based reasoning, case-based reasoning, narrative-based reasoning and ontology-based reasoning have matured and been tested in real-world service applications, there is a trend that a combination of different technologies need to be investigated in order to remedy the limitations of a single technology. For example, a commonly accepted limitation of rule-based reasoning is its scalability, i.e. when the total number of rules in the knowledge base increases, the time needed to infer also considerably

increases (Wakulicz-Deja et al., 2011). However, this drawback can be rectified by a combination use of rule-based reasoning together with clustering technology, i.e. by clustering similar rules to form distinct clusters of rules, the time needed for inference can be greatly reduced. Apart from the speed, accuracy has been an important issue to most reasoning technologies. Future research should spend more effort in verifying knowledge (Zaraté, 2013), for example the rules in the knowledge base should be validated by experts. The need for the knowledge verification becomes even more critical in clinical service KBDSS since a single piece of incorrect or inaccurate knowledge could result in a dangerous or wrong recommendation in turn could cause harm or safety issue to patients (Cesario and Esposito, 2012). A third challenge for reasoning technologies is how to incorporate the uncertainty of knowledge in KBDSS. Recent research has shown that by integrating existing rule-based reasoning or case-based resoning with fuzzy logic and artificial networks can enhance the reasoning performance in terms of uncertainty (Yang et al., 2011), which should remain as a hot topic for future service systems research. Finally, because of the intrinsic nature of incompleteness of knowledge, neither domain knowledge nor contextual knowledge is static or complete, as knowledge itself evolves all the time we would never have complete knowledge of a decision problem or solution at a time. In parallel, reasoning technologies to infer new knowledge based on exiting knowledge captured in the knowledge base should address this issue of evolution (Huang et al., 2011).

Recommendations for the development of KBDSS in service decision making:

Because of the fact that service industry aims to best serve and help public, community, and target customer groups, decision makers need to allow service users' participation and take into account service users' needs, requirements and their preferences in service decision making context, subsequently service systems need to emphasize both the use of communication and collaboration, as well as decision models (Zarate, 2013). It is important for KBDSS supporting service decision making to address knowledge sharing between the service providers and service recipients (either the general public, community or customers). It has been well acknowledged that the difficulty of knowledge sharing lies with the sharing of tacit knowledge, especially when decision makers come from very different background and confusing terms (such as business intelligence, enterprise information portal, communities, groupware, knowledge management and knowledge network) are being used simultaneously. When substancial knowledge-based intangibles (including people's abilities, professional knack, trade secrets, routines – unwritten rules of individual and collective behavior patterns) are available around, but the contextual knowledge is not well defined, it would cause great cognitive burden to decision makers (Grundstein, Rosenthal-Sabroux and Pachuski, 2003). To address the above issues, existing research has investigated and proposed solutions to the development of interactive learning environment to encourage knowledge transfer across disciplines, use of overlapping teams and joint learning. Further research is needed to develop typologies that can facilitate more effective sharing of tacit knowledge by integrating core elements including trust and care, leadership charisma, knowledge culture, concept ba and social network analysis (Shaqrah, 2010). By developing the typology and adopting it into knowledge-based service systems, the right communication and collaboration infrastructure will be provided to support knowledge flow in service decision making. So far, there is very little research published to address the knowledge modelling and reasoning mechanisms that are particularly suited to foster communication and collaboration to support participant-oriented service decision making, even though some knowledge artefacts as tools have been developed for collaborative user-driven design (Lindgren, 2012). Substancial opportunities exist for future research in integrating mature knowledge modelling and reasoning technologies into functioning KBDSS that can support participant-oriented service decision making scenario, especially in real world decision practices such as in medicine, public service, IT service, customer service and other real service decision cases. As a first step, we suggest that new knowledge modelling and reasoning technologies that aim to support service decision making should seriously consider methodologies such as knowledge chain management and multi-stakeholder approaches.

In terms of application domain, there is substantial opportunity to explore KBDSS in new service industries and sectors other than the domains reviewed in this paper. Inside the healthcare domain, future research needs to better address the integration of knowledge from various healthcare stakeholders such as doctors, nurses, patients, carers and the community, so that more coherent healthcare services can be provided across various activities including clinic diagnosis, treatment, home care, community support, and follow up actions (Montani, 2011). In the customer service domain, knowledge about customer and markets, product design and production, as well as maintenance and end-of-life treatment should be integrated in the knowledge base, and the KBDSS should enable the smooth flow of knowledge across the supply chain to foster the emerging knowledge chain management technologies (Liu et al., 2013). In the public service area such as e-government, further research has been identified in enhancing the capture of user profiles and their knowledge, and in being able to reason based on user profiles in order to provide more personalized and more inclusive services to citizens, especially to include those who need special care (such as because of infectious diseases) or have disabilities which cause mobility difficulties (Timmons, 2013).

There is no doubt that Web technologies have already made an impact on service systems – enabling the movement towards e-services in recent years (Liu et al., 2008). Along with the fast pace of semantic web, cloud computing and social networks moving forward, KBDSS originally developed for offline or local use will have great challenge from migrating to new open service platforms in order to take the full advantage of the Web technologies (Martínez-García et al., 2013). Some of the most often mentioned side issues associated with the Web-based service systems (no matter what types of knowledge modelling and reasoning technologies they are based on) include public, community and customers' privacy and safety, which should be a continuous interest of many KBDSS researchers (Zarate, 2013).

6. Limitations and Conclusions

This review paper focuses on the recent development on relevant technologies and service application domains of knowledge-based decision support systems (KBDSS). It complements a number of recent survey papers in the literature which were focused on specific, related areas, such as the integration of knowledge based-systems and DSS (Liu et al., 2010), ontology engineering (Easton, Davis and Roberts, 2011), contextual knowledge in medical CBR systems (Montani, 2011), and service science and innovation (Paton and McLaughlin, 2008). However, this paper brings together knowledge modelling technologies, reasoning and inference technologies, and Web-based technologies together with application domains in healthcare service, public service, IT service and customer service, by eliciting the links across different technologies and application domains. Therefore, this paper extends the review to a much broader picture and provides a synergistic view of KBDSS with more complex composition for service systems. Recommendations for future research are provided for the development of future KBDSS in general and in particular to support cases of service decision making. Nevertheless, one limitation of this work is that this study is with "ISI Web of Science" and it allows to a comprehensive analysis. In order to propose a systematic analysis, an alternative approach would be to integrate an analysis with Google.

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