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A Review Clinical Decision Support System using Ontology

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Abstract

A decision support system (DSS) is an intelligent system by which a decision support is provided for decision-making purpose. DSS extensively requires a representation of domain knowledge to apply reasoning methods that help in reaching new knowledge for decision support. Due to the benefits of Ontology compared with database system, it considered as knowledge representation in several DSS. DSSs have been extensively addressed in many research like healthcare, therefore it was named Clinical Decision Support System (CDSS). In this paper, a review on reasoning methods that has been utilized on CDSS has been conducted. The review is achieved through comparing and analysing the benefits and drawbacks of CDSS reasoning methods as well as surveying the current reasoning methods used in ontology based CDSS. After analysis, it has been revealed that the integration of the Case-Based Reasoning (CBR) method and Rule-Based Reasoning (RBR) methods facilitates the operation of CDSS to mimic clinical staff members. This integration is recommended since the CDSS will contain the two sources of knowledge which are domain knowledge and knowledge from historical cases. Furthermore, the review shows that ontology has been used in several CDSS but still not been integrated with CBR and RBR.

Keywords: *CDSS, Knowledge, Reasoning, ontology*

1. INTRODUCTION

A decision support system (DSS) is an intelligent system, which is currently introducing decision support for organizational decision-making purposes. Decision support represents the mechanism of retrieving new knowledge from the collection of data has been fed to the system. This new knowledge will be integrated with human knowledge later for decision-making (Hwang et al., 2018). The knowledge denotes familiarity, awareness and understanding of information extracted from data, which leads to extracting new knowledge (Rowley, 2007; Hwang et al., 2018; Ghasemaghaei, 2019). Thus, the required knowledge for decision support comes after two important levels which are: Data Level (DL) (an organized and related raw fact that has not been processed yet to reveal their meaning), and Information Level (IL) (the process of retrieving the meaning behind relations between raw data) as Rowley (2007) stated. In other words, decision support required knowledge, information and data; by which it needs to translate data into information and lastly reaches knowledge, as shown in Figure 1. The evolution of the decision support systems has been associated with the development of data since its inception in 1960. The literature about the history of database has been studied to investigate the way for incepting DSSs.

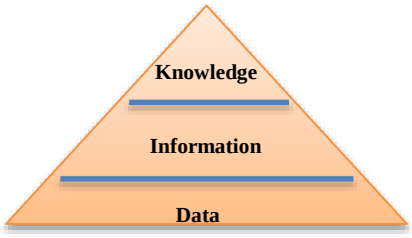

Fig. 1. requirements for decision support (Rowley, 2007; Kisilevich, Keim et al., 2013;Ghasemaghaei, 2019)

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2. LITERATURE REVIEW

Currently, NoSQL database is developed to address the challenges represented by big data (Hashem et al., 2015) and it has 4 main approaches as shown in Table.1. The 1st approach is the key value (KV), which is the simplest version of all the databases, where data relations are opaque. It does not have query languages, so KV database operates in DL (Escriva et al., 2012). The 2nd approach is document database, which stores data in tagged documents in key-value pairs. Thus, document database introduced sophisticated inquires and brought the KV database to IL. The 3rd approach, column database by which high performance on aggregation queries of data was achieved. In addition, it has the benefit of fast data loading for big data. Even though column database is considered as a vital improvement after KV and document database, it is still inadequate in providing any knowledge about its entities (operates in IL). The 4th approach is the graph database, which shines through giving the same importance to raw data and its relationships. Graph database brought data model abstractions closer to the method that humans used to handle knowledge (Karagiannis & Buchmann, 2018). This is applied through linking data together directly via relationships, which allow retrieving data in one operation. Graphs are considered as efficient means to visualize and represent real-world data by providing solutions to many real-time scenarios that can be simulated and implemented by using graph databases. Also they are considered as efficient in graphs query with multiple attributes, representing different domains of knowledge (Hor et al., 2018). Therefore, graph database represents the knowledge behind the body information and facts about specific subject. Thus, the main requirements for decision support systems are available in graph database.

Table1. Comparison between data types and methods used in storing relations between data

Types of systems	**File based system**	**Database system**		
Category	**Traditional** (1960s)	**Early** (mid 1960s to early 1970s)	**Conventional** 1970s	**Current** (mid to late 2000)
Data description	Structured	Structured	Structured (relational)	Unstructured (non-relation)
Method used to define relations	First-order logic	First-order logic	SQL	NoSQL 1. Key-Value. 2. Document. 3. Column. 4. Graph
Data model	First-order logic	1. hierarchical Network	ER model	1. Jeson. 2. XML 3. Flat model. 4. Traversal
Languages used	C, C++, COBOL	COBOL	Oracle, MYSQL	MongoDB, Riak, Oracle NoSQL Database
Knowledge available Operate in (DL, IL, KL)	No (DL)	No (IL)	No (IL)	1. Key-Value (DL). 2. Document (IL). 3. Column (IL). 4. Graph (KL).
Collection of Knowledge representation	Scratch	Scratch	Scratch	From scratch except graph database from (Open sources reusable knowledge Graphs)
Rules for decision-making	Logic and AI algorithms	Logic and AI algorithms	Logic and AI algorithms	Logic and AI algorithms

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advantages	Stores data in computer and facilitates searching for specific data	Allow searching and manipulating data without restrictions in queries	can store and inquire about bigger size data compared with all previous types	• Can model structured and unstructured data. • Graph database operates in KL
disadvantages	• Depends on predefined fixed queries to retrieve data. Operates in DL	• Insufficient when sparse data used. Operates in IL	• Still lack in representing and querying complex connections. • Operates in IL	Graph database operates in KL but still need to be modified or integrated to improve interpretation abilities.

2.1 Differences between Ontology and Database

(Faucher et al., (2008) stated that a key characteristic of KL is the ability to drive new knowledge from the old knowledge. This ability needs to feed the old knowledge with interpretation about the represented concepts and relations. This interpretation is introduced through a semantic technology, which is defined as the meaning and interpretation of words, signs, and sentence structure. The combination between the graph database and semantic technology results in an improved knowledge representation schema, which is ontology (Euzenat & Shvaiko, 2007). Ontology is a formal description of knowledge as a set of concepts within a domain and the relationships that hold between them. It is formally specifying components; such as individuals (instances of objects), classes, attributes and relations; as well as, restrictions, rules and axioms. Moreover, it has advantages such as (1) the introduction of a sharable and reusable knowledge representation about the domain, (2) the addition of new knowledge about the domain, (3) the provision of more meaningful querying interface than database, (4) its flexibility to apply rules to find hidden information, which leads to better result (5) its ability to solve the knowledge gap in data and information levels, through applying different rules by inference engine, as shown in the comparison at Table 2.

Table 2. Comparison between ontology and database (Munir & Anjum, 2018)

Comparison in terms of	**Ontology**	**Database**
Knowledge available	Directory or build by human	From scratch except graph database from (open sources reusable) knowledge Graphs)
world assumption	Open world assumption (OWA)	Closed world assumption (CWA)
Missing information	Treated as unknown	Treated as false
name assumption	Individuals may have more than one name	individual has a single, unique name
Schema behaves	is large and complex	simple and smaller
Rules for decision support	Inference engine mechanism	Logical rules of AI algorithms

Based on the aforementioned advantages of ontology, especially its operation in knowledge level, it is recommended to be used in DSS as a knowledge representation. DSSs have been extensively addressed in many research like healthcare, so it was named Clinical Decision Support System (CDSS) (Evchina et al., 2015; Maarouf et al., 2017; Spoladore, 2017; Shoaip etal., 2019).

2.2 Clinical Decision Support System (CDSS)

Clinical Decision Support System (CDSS) refers to an intelligent system, which is currently introducing decision support for clinicians to help in decision-making later as diagnosis and proposing treatment plan, through the interaction between the clinician and CDSS (Bookman & Raja, 2017). The CDSS in the healthcare field has the benefit of delivering the right information to the right people. Whereas the CDSS passes this information through the right channels in the right intervention formats at the right points in workflow (Luxton, 2015; Kim, 2018). Moreover, CDSS has the advantage of integrating into the clinical workflow rather than as a separate login or screen, in addition to its dependency on electronic based templates rather than paper (Kim, 2018; Khalifa, 2014). Thus, CDSS is considered as an increment to electronic charting and could potentially lead to improving patient care (Pandey & Mishra, 2009). Within the last years, the CDSS systems improved the process of medical care in 52–64% of studies across several reviews as revealed by Roshanov et al. (2013). In addition Roshanov et al. (2013) stated that only 15–31% of those evaluated for impact on patients' health showed positive impact on patient outcomes. Moreover, it has been found that there is an association between success and automatic provision of CDSS giving recommendations and not just diagnosis (Roshanov et al., 2013). This leads to improvement in the outcomes of clinical care that is utilizing the CDSS. CDSS consists of two main parts which are Knowledge base and inference engine, as shown in Figure.2.

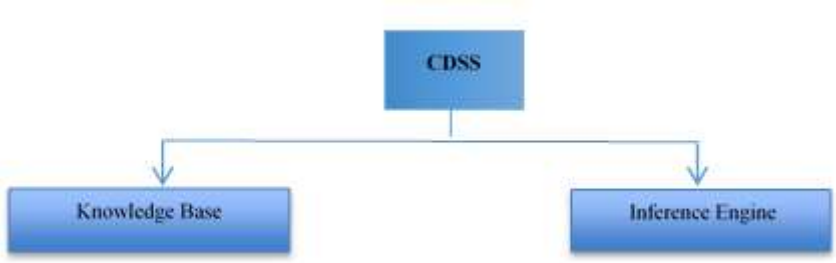

Fig. 2. Components of CDSS

2.3 Knowledge Base

The knowledge base (KB) contains the knowledge which can be scratched from database systems or can be reused from ontology. For the inference engine, it considers any inquiry about a problem and starts to think about it like humans to deduce new knowledge (Jiang et al., 2017; Shoaip et al., 2019). This is done by examining the KB to solve the problem and extract decision support within the domain. The process of providing powerful methodologies, tools, and techniques for manipulating KB to make an inference, then provide decision support, is the reasoning process (Chen et al., 2019). Thus, reasoning can be considered as a true power and an important task performed by the inference engine of the CDSS. There are three common reasoning methods that have been used which are (Case-Based Reasoning (CBR), Model-Based Reasoning (MBR), and Rule-Based Reasoning (RBR)) (Pandey & Mishra, 2009; Summers, 2016; Shoaip et al., 2019), as shown in Figure.3. The advantages and disadvantages of these methods have been illustrated in Table.3.

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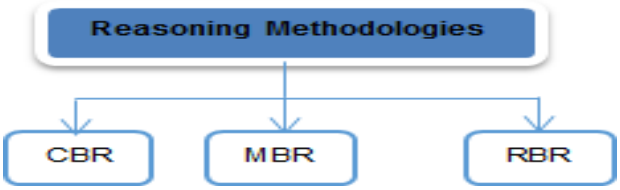

Fig. 3. Reasoning Methods

Table.3: Comparison between reasoning methods (Pandey & Mishra, 2009; Shoaip et al., 2019; Summers, 2016)

Method	Main concept	Advantages	Disadvantages
RBR	a rule which contains an (if) and a (then) component is used to represent the task	• Modularity. • Uniformity • Flexibility and variety in use. • Have the facility of Explaining the reason behind the result. • Similar to human thinking process. • Ability to express general knowledge. • Proven	• Sometimes rules have exceptions. • Missing information or unexpected data values is not easy to be handled. • Difficulty in representing informal information • Inference efficiency problem. • The rules can be tasked specific (no general rules) • No learning. • Difficulty in maintenance of large rule base. • No memory.
MBR	The structure and behavior of the system is simulated by a model	• Depend on the structural knowledge in problem solving. • Very vigorous. • Explains the reason behind the result. • a conceptual explanation of error is provided to human user	• Experiential knowledge in MBR is not enough. • Not efficient in implicit domain model or uncertain knowledge. • Tend to be complex because it operates at a high level of detail. • Handling the exceptional situations is difficult. • Faces difficulties in modeling because of lack in model builders. • Need for reusable libraries. • Need for integration with other methods
CBR	Reused the previously experienced in solving future problems based on a problem situation	• self-evident • Does not need knowledge elicitation for rules creation (use cases information in rule elicitation). • Learning done by acquiring new cases. • Can solve problems with many alternative solutions. • Ability to express	• Need large memory for all cases and. • high cost search • Take long processing time • Adaptation needs to be improved more. • Inability to express general knowledge. • Face difficulties in adaptions.

specialized knowledge.
- Have inference efficiency.
- Applicability
- Modularity
- Self-updatability

- Problem of competence gap

3. METHODOLOGY

The strength and weakness of reasoning methods can be analyzed based on their ability to generalize knowledge (Osbeck, 2014), learn (Griffin et al., 2012), inference (Jiang et al., 2017), adaptation (Wasylewicz & Scheepers-Hoeks, 2019), and consume low computational cost (memory and processing time) (Jiang et al., 2017; Summers, 2016) as shown in Table 4. This analysis has been conducted based on studying several reviews about DCSS starting from 2009 to 2019 in addition of analysing serve.

4. DISCUSSION AND ANALYSIS

After analysing the advantages and disadvantages of each method, it has been noticed that the CBR is the best, in terms of learn, inference, adaptation and computational cost compared with others. On the other hand, CBR is inefficient in getting general rules, which can be integrated with RBR that is effective in getting rules for specific tasks.

Table.4: Comparison between RBR, MBR, CBR in terms of ability to generalize knowledge, learn, inference, adaptation and consume low

Criteria / **Importance**	**RBR**	**CBR**	**MBR**	**limitation**
Generalizing knowledge To get general rules describing the knowledge for reasoning purpose (Osbeck, 2014)	✓	×	×	• Rules sometimes have exceptions. • Cannot handle the missing information easily. • Rules can be task specific.
Learn: In medical filed, the previous patient cases useful in learning rules which help in diagnosis new patient	×	✓	×	Not sufficient enough in getting general rules from the previous patients data
Inference: Get new knowledge from the domain knowledge based on the input	✓	✓	✓	The three methods can perform inference but vary in efficiency based on the other factors affects inference such as (learning, generalizing knowledge and adaptation)
Adaptation: Modify the input of the inference engine based on the cases and the domain knowledge which helps to get better consultation	×	✓	×	CBR can perform adaptation but still face some difficulties on it

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Computational cost: Use less memory and less time	✓	×	×	RBR has no memory so the computational cost is lower compared with CBR and MBR. MBR is the highest computational cost in time and memory compared with the CBR and RBR.

4.1 Rule Base Reasoning (RBR) MODEL

Traditionally rule-based reasoning was performed by a process of chaining through. If then rules (Shortliffe et al., 1975), Searching in hierarchical manner (Hudson & Estrin, 1984), Backward Channing and Forward Channing ((Heart, 1988), Matching in a frame ((Wah & Muniandy, 2014), Bays rules (Diez et al., 1997), Backtracking (Marling &Petot, 1999) and Bayes' theorem (Lejbkowicz et al., 2002). Indeed, each method has its strengths and weaknesses. However, logic was the most popular method because it is familiar to many people due to its long history, and due to its solid mathematical background ((Yang et al., 2004). Unfortunately, traditional logical rules are not always suitable for addressing human knowledge, particularly reasoning about knowledge involving uncertainty (Pandey & Mishra, 2009; (AbuAmr et al., 2019). Recently, RBR algorithms utilized ontology as KB representation in several medical applications as illustrated in Table.5. Unfortunately, RBR systems are lacking in specializing recommendations for individuals.

Table.5: RBR Model

Reference	KB	Reasoning Algorithm	Application
(Gaspari et al., 2009)	ontology	Forward chaining and backward chaining	Disability in multiple sclerosis (MS) clinical trials.
(Kukolja et al.,2010)	ontology	If then rules +Neural Network (NN)+ Genetic Algorithm (GA)	Treatment of Stress Related Disorders
(Esposito et al.2010)	ontology	First-order logic rules	home health monitoring
(Spaulding & Deogun, 2011)	ontology	Semantic Web Rule Language (SWRL)	Psychiatric Rehabilitation
(Kostopoulos et al., 2011)	ontology	SWRL	Facilitate healthcare professionals in personalized exercise prescription.
(Evchina et al., 2015)	ontology	Ontology based reasoner (Pellet reasoned)+SWRL	health monitoring of residents in assisted living applications
(Khattak et al., 2016)	ontology	If then rules	healthcare and life-care services
(Spoladore, 2017)	ontology	Ontology based reasoning +SWRL	Ambient Assisted Living and Work Reintegration domains
(Maarouf et al., 2017)	ontology	Ontology based reasoner+GDL	Assessment and Rating of Ataxia
(Alloni et al., 2018)	ontology	Mathematical calculation: Friedman's analysis / Fisher's exact test.	effectiveness of Parkinson disease treatment

4.2 Case Base Reasoning (CBR) MODEL

In CBR, the new problem is solved based on knowledge where the cases are considered as means of solving the new problem, suggesting means of modifying a solution that does not suit the problem, warning of possible failures, and interpreting a situation (Ali et al., 2016). CBR system has the ability of using specific knowledge extracted from previous problems instead of relying on general knowledge of the domain (Shoaip et al., 2019). As CBR system did not require an explicit domain model, plus it's like going to an experienced doctor. The CDSS that based on CBR methods and application is illustrated in Table.6. Decision-making based on historical cases is natural for clinical staff members, which is the main benefit of CBR systems over the RBR systems(Gu et al., 2017). Thus, the CBR systems resemble the human mind by using past experience in solving clinical problems. Unfortunately, the CBR missed another important source of knowledge in addition to historical cases, which is the domain knowledge (Saraiva et al., 2016). Moreover, it is axiomatic that the clinical staff members have the two sources of knowledge which are domain knowledge and knowledge from historical cases. Thus, CBR systems need support to integrate the domain knowledge especially in the medical field (Prentzas & Hatzilygeroudis, 2007).

Table.6: CBR model

Reference	KB	Reasoning Algorithm	Application
(Fan et al., 2014)	ontology	Similarity matching +back propagation algorithm and least square method	smart rehabilitation systems
(Riaño et al., 2012)	ontology	Navigation on case profile ontology using Jena	the Care of the Elder at Home
(Ceccaroni & Subirats, 2012)	ontology	k-nearest neighbor (k-NN)	Physical rehabilitation
(Robles-Bykbaev et al., 2015)	ontology	Partition Around Medoids (PAM) the mean-Manhattan binary distance (ManhDist	speech and language pathologists
(Robles-bykbaevt et al., 2016)	ontology	based reasoner+ Hierarchical Agglomerative Clustering (HAC)	speech and language pathologists

4.3 Model Base Reasoning (MBR) MODEL

Model-based systems model the system structure and functions being studied, which is considered as a great improvement in the decision support system (Biswas et al., 2014) as show in Table 7. Model-based method has been used in many CDSSs for different purposes. A model of abnormal behaviour, which includes collection of causes that associated with abnormal findings predictions is an example of model-based system that developed by (Lucas et al., 1999). Ontology has been extensively used in a model-based system for medical applications. ULSont is an example for a Model based reasoning model that designed to help the specialist in accessing the patients' information as well as making decision for patient assessment (Afandi et al., 2017). Most of these applications used the simple build-in ontology reasoners such as Pellet (Dogmus et al., 2015), FC++ (Berges et al., 2016) and OWL-DL reasoner (Riano et al, 2012).

Table.7: MBR Model

Reference	KB	Reasoning Algorithm	Application
Dogmus et al.,2015	ontology	Ontology based reasoning (Pellet)	Representing the available information about rehabilitation robots
Berges et al., (2016)	ontology	Ontology based reasoning ((Fact++)	assist rehabilitation processes
Subirats and Ceccaroni (2011)	ontology	Ontology based reasoning (PELET)	Functional disability rehabilitation

Afandi et al. (2017)	ontology	Ontology based reasoning (Pellet)	Upper Limb functional rehabilitation
(Quaglini et al., 2009)	ontology	Ontology based reasoning	Computerized Cognitive Exercises

5. CONCLUSION

A clinical decision support system (CDSS) is an intelligent system, which is currently introducing decision support for decision-making purposes. The decision support is applied by retrieving new knowledge from a knowledge base that should be fed to the system. Ontology is preferred to be used as knowledge base representation due to several benefits such as its ability to: provide a sharable and reusable knowledge representation about the domain, add new knowledge about the domain, provide more meaningful querying interface than database and apply rules to find hidden information, which leads to better result. The knowledge base is examined through reasoning method to deduce the new knowledge. Three common reasoning methods have been used in CDSS. After the comparison between the current reasoning methods it is recommended to integrate the CBR and RBR in the CDSS to utilize the advantages of both methods. Furthermore, it is recommended to develop an ontology based CDSS that integrates both methods in reasoning.

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