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Abstract. In order to enhance the quality of care, healthcare organisations are increasingly resorting to clinical decision support systems (CDSSs), which provide physicians with appropriate health care decisions or recommendations. However, how to explicitly represent the diverse vague medical knowledge and effectively reason in the decision-making process are still problems we are confronted. In this paper, we incorporate semiotics into fuzzy logic to enhance CDSSs with the aim of providing both the abilities of describing medical domain concepts contextually and reasoning with vague knowledge. A semiotically inspired fuzzy CDSSs framework is presented, based on which the vague knowledge representation and reasoning process are demonstrated.

Keywords: Semiotics, Fuzzy logic theory, CDSSs, Knowledge representation, Knowledge reasoning

1 Introduction

Clinical decision support systems (CDSSs) – known as the provision of patient-specific assessments or recommendations to support the clinical decision making [1], have been increasingly applied in various healthcare institutions. Previous studies have shown that CDSSs can improve the clinical practices [2], reduce serious medication errors and enhance the delivery of healthcare services. However, multiple challenges continue to impede the effective implementation of CDSSs. As vague information exists almost everywhere in the whole clinical decision making process, the interactions between organisational and technical factors should be considered when we design the CDSSs, especially during the representation and interpretation processes of the domain knowledge. Sources of vagueness or imprecision may be qualitative and quantitative. Qualitative vagueness is generated by lacking of precise measurements. For example, some symptoms (patients' facial expressions, feelings and behaviours) are usually described in some subjective terms. Quantitative vagueness is generated by lacking of precision in a measurement even when corresponding precise measurement exists. For example, the value of Body Mass Index (BMI) can be accurately calculated with height and weight. However, not everyone with a high BMI is obese, especially the one who exercises regularly.

Besides, knowledge is usually characterized by a high level of context-dependency [3] and evolvement [4]; therefore, it cannot be defined independently without their pragmatic meanings. Thus, without appropriately handling with these challenges, the CDSSs might not support the clinical practice effectively. In order to address the aforementioned issues, we draw a refined underpinning and methodology to offer an adaptive framework of CDSSs integrating with more accurate knowledge representation and interpretation mechanism. By integrating the organisational semiotics and fuzzy theory, the proposed framework of CDSSs allows describing medical domain concepts contextually and reasoning with vague knowledge.

The reminder of the paper is organized as follows. Section 2 outlines the related theoretical background and main previous researches. The subsequent section provides a detailed illustration of the semiotically inspired fuzzy CDSSs framework; especially the knowledge representation is designed and reasoning process is discussed. Finally, section 4 draws our discussion and conclusions.

2 Theoretical Background

The proposed hybrid framework integrates two techniques, namely organisational semiotics and fuzzy logic theory, which are shortly outlined in the following sub-sections.

2.1 Organisational Semiotics

Organisational semiotics (OS) is a particularly branch of semiotics related to organisations, business and the IT system. From the OS perspective, IT systems or computer-based systems can be seen as the inside layer of the formal system in the organisational onion as shown in Fig.1, that means only a small part of the entire organisation. Therefore, in the IT system analysis and design, the related informal and formal aspects of the business should be firstly understood. Based on this view, the effective implementation of CDSSs requires a clear understanding and modelling of the interactions among these three aspects.

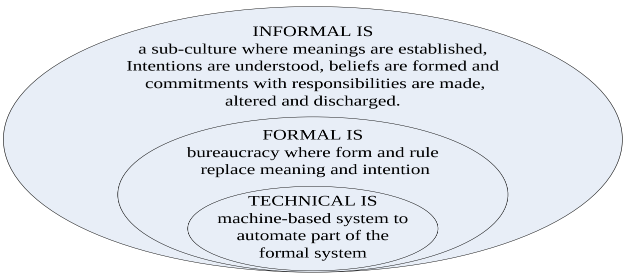

Fig.1. The organisational onion [5-6]

Moreover, the performance of CDSSs largely depends on its underlying knowledge base [7]. Stamper shares the view that knowledge is those signs interpreted at the social level of semiotic ladder (composed of physical word, empirics, syntax, semantics, pragmatics and social world), and it is equated with norms and attitudes [8]. Therefore, the explicit representation of knowledge should realize the mapping from the informal layer to the formal layer.

2.2 Fuzzy Logic Methodology

Fuzzy logic resembles human reasoning in its use of vague information to generate decisions [9]. Unlike classical set theory, fuzzy logic provides an alternative way of thinking about the complex system modelling, characterized with the membership of an element instead of the crisp value. The difference between the classical set and fuzzy set is shown in Fig. 2.

Definition 1. Fuzzy set A is described by some predefined range X (known as the universe of discourse) and the membership function μ_A, then

$$A = \{ (x_i, \mu_A(x_i)) \mid \forall x_i \in X, \mu_A(x_i) \in [0,1] \} \quad (1)$$

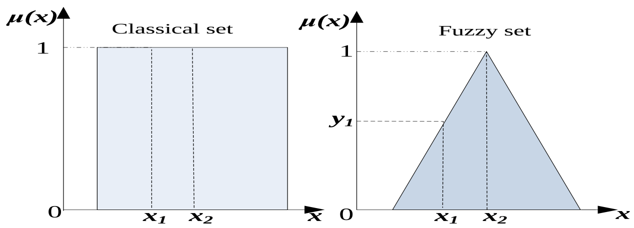

Fig.2. Difference between classical set (*left*) and fuzzy set (e.g. triangular membership function) (*right*)

Because of the inherent vagueness of the medical knowledge, fuzzy logic has been utilized in many medical applications, such as the fuzzy expert support system for coronary artery disease screening using clinical parameters [10], determining the caloric intake requirement [11], and monitoring the multiple sclerosis [12]. However, fuzzy logic theory has limited ability to elicit the variables/elements and reflect their contextual interpretation. Therefore, incorporating the semiotic approach into fuzzy logic is a candidate solution for conceptual and computational modelling, which allows for the explicit representation of the contextual interpretation [3] and ensures the effective implementation of CDSSs.

3 Semiotically Inspired Fuzzy CDSSs Framework

In this paper, we propose the semiotically inspired fuzzy CDSSs framework, which is shown in the Fig. 3. It is based on the organisational onion, which integrates the informal and formal factors during the IT system design process. Moreover, the use of fuzzy logic enables the quantitative representation with the aim of reducing the ambiguity of knowledge, so that the reasoning as well as the utilization of the vague knowledge can be more effective to support the decision-making.

As shown in the Fig. 3, the proposed CDSSs framework can be described in three levels: informal, formal and technical level.

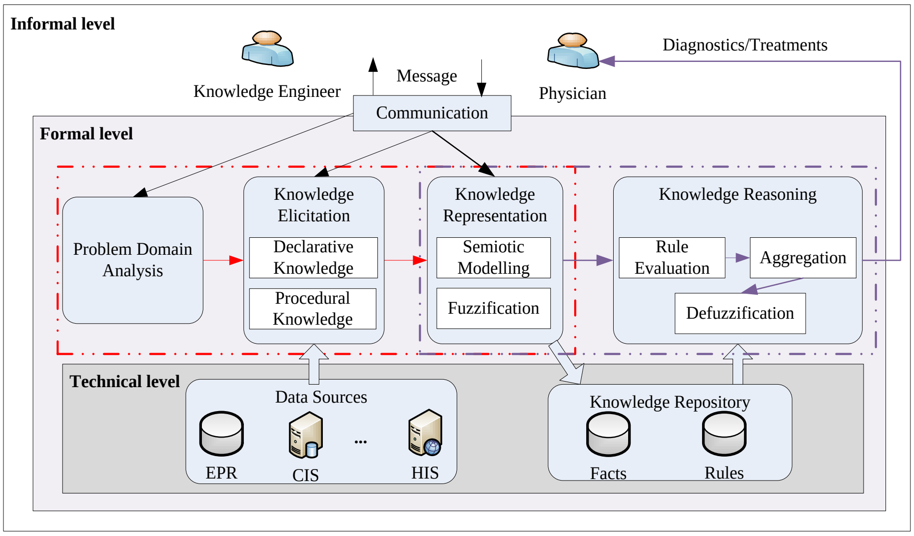

Fig.3. Semiotically-inspired fuzzy CDDSs model

(1) Informal level: We define system users as agents in this paper, e.g. physicians, nurses, any other healthcare professionals and knowledge engineers. In this paper, we just take two main perspectives (knowledge engineer and physician) to illustrate the mechanism of this model in Fig. 3. The shared beliefs and values on the medical quality improvement and accuracy decision support strategy through the treatment process will be established. In real scenarios, all kinds of agents have to acquire various related data and deliver them to the computer-based system. But the substantial common understanding and explicit representation of these inputs are definitely based on the communications/interactions between the informal level and the formal level. For the physicians, the communication also provides the preparatory work for the following knowledge reasoning and treatment/diagnostics recommendations.

(2) Formal level: including the problem domain analysis, knowledge elicitation, knowledge representation and knowledge reasoning. We analysis these modules following the activity lines for knowledge engineer and physician, respectively.

As what we have discussed above, a good and effective decision support system cannot be independent on its underlying knowledge base. Therefore, for the knowledge engineers, they will firstly conduct the problem domain analysis, which focuses on the understanding of the organisation from both the informal and formal perspectives and investigating of the potential problem to be dealt with. Subsequently, they will elicit clinical knowledge from multiple sources and represent them with formalized specifications. During this elicitation and representation process, knowledge engineers have to coordinate the formal aspects with many informal aspects in the organisation with the communication module. For example, different physicians may have different preferences on the diagnostic criteria or subjective assessments on the non-verbal expressions; they may also have different beliefs such as low healthcare cost, high quality healthcare services and low healthcare risks; therefore, all of the vagueness should be considered when constructing the knowledge repository. All the elicited knowledge can be classified along two axes: declarative knowledge and procedural knowledge [13]. In particular, declarative knowledge describes all kinds of medical domain concepts, their attributes as well as the interrelationships between the concepts and attributes. On the other hand, procedural knowledge specifies a set of prescriptions for actions in relation to certain types of conditions or conclusions to be drawn from the declarative knowledge. In this paper, we introduce the context analysis based on the semiotic triangle model to represent and interpret imprecise knowledge. Specially, declarative knowledge will be interpreted with the semiotic triangle model (section 3.1) and stored in the knowledge facts repository, while procedural knowledge will be demonstrated with fuzzy set theory (section 3.2) and saved in fuzzy rules repository.

For the physicians, their activity line includes the knowledge representation and knowledge reasoning. Knowledge representation mainly addresses the definition of membership according to own understanding and context. In this paper, we adopt the Mamdani-style fuzzy inference procedures [14] to implement the fuzzy system, mainly composed of fuzzification of input variables, rule evaluation, aggregation of the rule outputs, and defuzzification.

(3) Technical level: automate the well-defined work procedures of the fuzzy clinical decision support system. It is developed to read signs, re-arrange signs, process and finally display them. Multiple sources of knowledge in this research are also defined in this level: (i) clinical data derived from other current healthcare IT applications including electronic patient record (EPR), clinical information system (CIS), laboratory information system (LIS), picture archiving and communications system (PACS), etc.; (ii) existing clinical pathways and other business processes/procedures in use in hospitals; (iii) social knowledge or shared clinical experiences (recorded and observed) from community members; (iv) existing medical entities (basic statements about the medical concepts) and public medical classification terminologies such as SNOMED CT (Systematized Nomenclature of Medicine Clinical Terms); (v) medical educational resources for practitioners and (vi) academic resources like medical literatures and case studies. Besides, the implementation of knowledge repository including the facts and rules are built according to the informal and formal factors.

Obviously, the computer-based system presupposes a formal system, just as the formal system relies on an informal system. Information flow and interactions among these three levels should be considered in the design of the CDSSs, especially facing the inherent vagueness of the medical knowledge.

3.1 Knowledge Fact Representation

In this sub-section, we will further discuss the conceptual modelling in a broader context of knowledge fact representation, mainly focus on the understanding and interpreting of medical knowledge.

An explicit representation of the medical knowledge is critical for the proper functions of CDSSs. However, the elements of medical knowledge must be defined within a context of their usage for a specific patient, at a specific time, for a specific purpose, by a specific healthcare professional. Although many existing clinical diagnostic criteria and domain terminology (e.g. SNOMED CT, ICD-10) indicate the diagnosis and treatment for diseases, the definition of domain concepts is not context-aware and still requires the communication in the creation of their meanings, especially for the inherent characteristics of medical knowledge such as the vagueness and context-dependency. Therefore, in this paper, the knowledge representation approach based on the peircean semiotic triangle (object, representamen and interpretant) is introduced, as shown in Fig. 4. We define the object as multi-dimensional variables /concepts including the quantitatively measurable variables and qualitative (subjective) ones, meanwhile, the sign stands for several specific measurements such as multi-parameters on various types of instruments/sensors, laboratory report, CT, observations, questionnaires and psychological scales. Interpretant is the most complex notion in this model and it provides not only semantic meaning but also pragmatic significance. The intepretant is identified by the context in several dimensions: agents (e.g. healthcare professionals, nurses, patients), intentions (e.g. treatment, assessment), preferences (e.g. subjective assessment for the measurements), and temporal information. Therefore, the meanings of any medical elements will be quite different according to their possible interpretations.

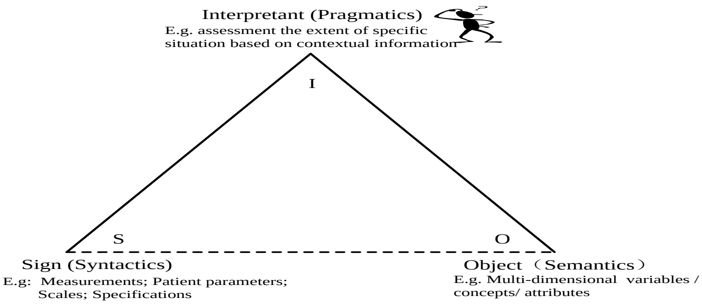

Fig.4. Semiotic triangle for knowledge fact representation process (adapted from Peirce's theory)

For the qualitative measurable variables mentioned above, for example, physical activeness, dietary habits, sedentary behaviour and quality of life, they are quite difficult to define, measure, or quantify. Even for some quantitatively measurable variables, e.g. age, the group they belong to might be more meaningful than the actual values for the healthcare professionals. Besides, several cut-off values for existing diagnosis criteria are often arbitrarily established. For example, the value of Body Mass Index (BMI) greater than or equal to 30 indicates obesity; however, somebody whose BMI equals to 29 and be with small muscle mass may means higher fat than a muscular person with BMI = 32. Therefore, fuzzy logic theory is adopted in the interpretation process.

Based on the analysis above, a piece of knowledge fact can be represented by a quintuple:

$$KF = \langle C, T(C), U, I(P, H, M, T) \rangle \quad (2)$$

Where C is a set of related concepts/variables; $T(C)$ is the set of terms for C, U is the universe of discourse; I, the function of P, H, M and T, means the interpretation process; P stands for a specific patient; H stands for a specific health professional; M represents the possible measurements; T means a specific time. Set of the terms will be identified for each concept, such as *´very mild´*, *´mild´*, *´moderate´*, *´severe´*, and *´extremely severe´* for the concept of *stress*. It is also worth mentioning that attributes of the concepts can also be defined when required, e.g. *frequency* and *intensity* for the concept of *stress*. The measurements are mapped into these defined terms according to the interpretation process. With the function I, crisp assessment value for various measurements (especially for the qualitative measurable variables) will be produced as the input data of the fuzzy CDSSs.

3.2 Fuzzy Reasoning Process

The medical domain knowledge must be translated into a computational model in order to be identified by the computer-based system. This sub-section will describe the fuzzy reasoning process in four steps, namely fuzzification, rule evaluation, aggregation, defuzzification, as shown in Fig. 5.

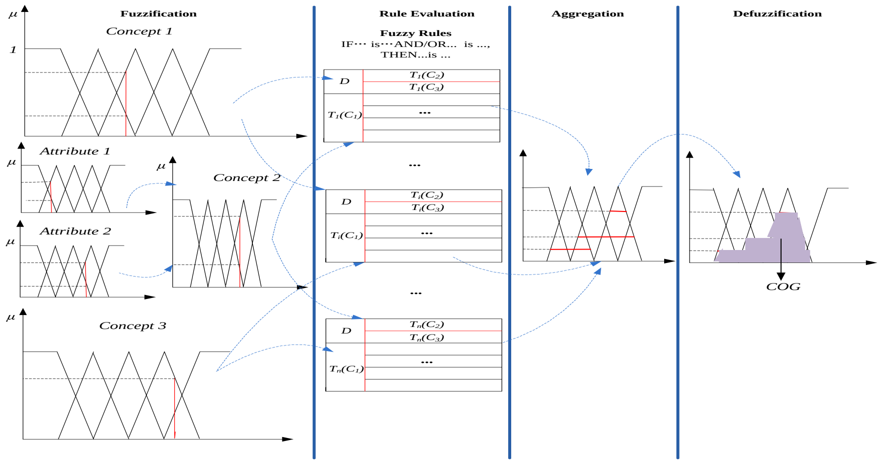

Fig.5. Sketch of the computational modelling process (Take three-input process as an example. *D* means the output concept for final decision, which is also described as a fuzzy set)

Step 1: *Fuzzification.* With the interpretation process, not only the quantitative variables but also the qualitative ones will be assigned an appropriate crisp value belongs to the universe of discourse. In this step, crisp input values will be converted into corresponding fuzzy terms with appropriate membership degree values. Fig. 6 shows the membership functions for five defined terms of concept "*physical activeness*". The membership functions will be constructed with the communication between knowledge engineers and healthcare professionals, with the consideration of the context information.

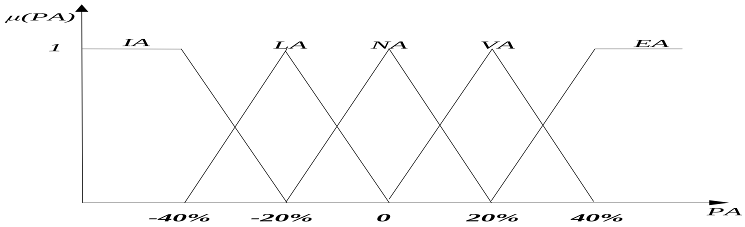

Fig.6. Example for the membership functions of physical activeness.

In Fig.6, the PA axis refers to the universe of the discourse for the physical activeness, whereas the $\mu(PA)$ axis represents the degrees of membership in the [0, 1] interval. The terms of the subset PA are $\{IA, LA, NA, VA, EA\}$ where IA = inactive; LA = lightly active; NA = neutral active, VA = very active; EA = extremely active. Trapezoids and triangles are chosen to represent the membership functions, e.g., the membership function of LA is triangular (-40%,-20%, 0).

Step 2: *Rule evaluation.* In this step, multiple fuzzy inputs generated last step can be seen as the antecedents of the fuzzy rules. All the possible values for these antecedents will be calculated according to the defined fuzzy rules. These fuzzy rules are developed by integrating the experiences of healthcare professionals and those of knowledge engineers with the consideration of the problem characteristics. The formal format of fuzzy rule is "If antecedent is…, then consequent is …". Take the type-2 diabetes mellitus (T2DM) prediction as an example. If we adopt *BMI, Physical activeness and Stress* as three variables, therefore, one typical knowledge rule can be: If *BMI* is *very high* and *Physical activeness* is *inactive* and *Stress* is *extremely severe,* then *the risk for the T2DM* is *very high*. Especially, the "S*tress*" variable here can be qualified with two attributes of this concept, namely the *has-intensity* and *has-frequency*. The reasoning process also applies the fuzzy logic, e.g. If stress *has-intensity* is *extremely high* and stress *has-frequency* is *almost-all-the-time*, then the *stress* is *extremely severe*. Part of the classifications of fuzzy rules repository is shown in Table 1.

Table 1. Classifications of fuzzy rules (based on our previous work [15-16] and background)

Rule repository classification	***Potential application scenario***
Clinical diagnosis	Evaluation of a patient's condition; Evaluation of clinician's suggestions.
Preventive reminders	Health maintenance; Clinical prevention for certain diseases.
Nutrition	Caloric intake requirement; Form healthy dietary habits.
Behaviour recommendation	Physical activity and calorie consumption.
Examination	Recommended examinations for certain diseases
Consultation	Assessment for the mental disorders.

Suppose we have predefined n variables, according to membership functions for a group of defined terms, 2^n fuzzy rules in one form can be activated at the same time. The values of consequents for these activated rules can be calculated with Mamdani Operator [11], shown in Eq. 3.

$$\mu(V_1, V_2, ..., V_n) = \phi\left[\mu_{V_1}(v_1), \mu_{V_2}(v_2), ..., \mu_{V_n}(v_n)\right] \\ = \mu_{V_1}(v_1) \wedge \mu_{V_2}(v_2) \wedge ... \wedge \mu_{V_n}(v_n) \tag{3}$$

Step 3: *Aggregation.* In this step, all the results of consequents in step 2 will be integrated into a final fuzzy set with the aggregation operator, union ($\vee$). The process can be seen clearly in the Fig. 5 with the comparison of aggregation step and defuzzification step. The shade area in the defuzzifation diagram indicates the final aggregation result.

Step 4: *Defuzzification.* It is the final step for the computer-based system. In this step, linguistic or crisp value (if required) can be obtained. The most popular technique to convert fuzzy set into a single number is calculating the centre of gravity (COG) of the fuzzy set (shaded area in Fig.5), using Eq. 4.

$$COG(A) = \frac{\int_a^b \mu_A(x)\ x\ dx}{\int_a^b \mu_A(x)\ dx} \tag{4}$$

Where A represents the final aggregation fuzzy set, its universe of course is $[a, b]$.

4 Discussion and Conclusions

CDSS is increasingly important in supporting the clinical practices including prevention, diagnosis, treatment, evaluation and long-term care. Its performance can be affected by the communication between the business and technical factors in the healthcare organisations, especially because of these characteristics of medical knowledge such as vagueness and context-dependency. In this paper, a semiotically-inspired fuzzy CDSS framework is proposed, while two key points, namely vague knowledge representation and reasoning, are illustrated. The innovation of this study is twofold. Firstly, we emphasize the role of informal factors with the organisational onion in the design phase and operation of CDSS, as the vagueness and imprecision are the intrinsic characteristics of medical knowledge. The contextual information and communication are considered in their definition and interpretation processes. Specifically, we explain the knowledge presentation process with semiosis and construct the knowledge representation model. Secondly, we modify the reasoning process with the semiotic thinking to support CDSS, which is also the formal part of the proposed framework. Although the application of fuzzy logic in healthcare is definitely not new, integrating the fuzzy logic and semiotics in an organisational perspective is necessary for the decision-making process, especially in the definition of membership functions of various linguistic variables and their attributes. Besides, we have applied this approach in a CDSS for the purpose of supporting the diagnosis and treatment of T2DM in a clinical setting in China.

On the other hand, this research faces some potential challenges. The most obvious one would be the computational efficiency. The active knowledge rules will be much more complicated with the increasing of the input variables and the complexity of membership functions. Therefore, future work could involve how to elicit the most significant variables and how to further refine the knowledge rule. Moreover, some potential application area could be integrating the multiple sensors with the proposed framework with the aim of providing a wider range of support, such as the homecare and mobile hospital for the chronic patients.

Acknowledgments. The research is supported by the Beijing Municipal Natural Science Foundation under Grant 9133020 and scholarship program sponsored by China Scholarship Council (CSC). Special thanks to Hongqiao Yang, the Director of the Information Centre of Hospital 309 of People's Liberation Army, China, for providing the research background and valuable guidance.

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