Fuzzy ontology for patient emergency department triage

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Abstract. Triage in emergency department (ED) is adopted procedure in several countries using different emergency severity index systems. The objective is to subdivide patients into categories of increasing acuity to allow for prioritization and reduce emergency department congestion. However, while several studies have focused on improving the triage system and managing medical resources, the classification of patients depends strongly on nurse's subjective judgment and thus is prone to human errors. So, it is crucial to set up a system able to model, classify and reason about vague, incomplete and uncertain knowledge. Thus, we propose in this paper a novel fuzzy ontology based on a new Fuzzy Emergency Severity Index (F-ESI_2.0) to improve the accuracy of current triage systems. Therefore, we model some fuzzy relevant medical subdomains that influence the patient's condition. Our approach is based on continuous structured and unstructured textual data over more than two years collected during patient visits to the ED of the Lille University Hospital Center (LUHC) in France. The resulting fuzzy ontology is able to model uncertain knowledge and organize the patient's passage to the ED by treating the most serious patients first. Evaluation results shows that the resulting fuzzy ontology is a complete domain ontology which can improve current triage system failures.

Keywords: Fuzzy Ontology, Uncertainty, Medical Ontology, Patient Triage.

1 Introduction

An effective triage in emergency departments (ED) can limit overcrowding situations and enhance the care quality and the slightest mistake increases the risk of mortality [1,2]. Recently, some studies have focused on improving the triage of patients by employing new technologies [3,4] refining collaboration and communication strategies [5,6]. The major disadvantages of these systems are the processing of textual and unstructured data and the representation and manipulation of medical knowledge considering the imprecision of these data. Structured triage protocols are already being widely used in the ED [8]. These protocols are tools aimed at prioritizing patients according to

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some established criteria such us the emergency severity index (ESI). The ESI classification was created in order to facilitate the patient triage, and thus to improve the patient throughput and disposition decision [7]. Nevertheless, this triage system depends greatly on nurse's subjective judgment, then the risk of error is very high. In this context, Wunch et al. [13] have demonstrated that ontologies are a potential solution to the problem of patient triage. Ontologies describe knowledge in terms of concepts, objects and data properties and relationships between concepts. In the literature, to facilitate biomedical research and standardization of the medical vocabulary, several ontologies and knowledge bases have been defined, such as the Systematized Nomenclature of Medicine Clinical Terms (SNOMEDCT), International Classification of Diseases (ICD), Disease Ontology (DO), Symptoms Ontology (SYMP). In this context, some models for supporting healthcare professionals in patient triage process exist in the literature [10,11,12]. For example, the model of Farion et al. [9] deals with heterogeneous clinical decisions. The main objective of this kind of system is to improve medical decision making in triage and to facilitate data sharing between users. However, the problem of missing and imprecise data and knowledge is still one of the major limitations of medical systems. Therefore, the use of fuzzy subset theory and fuzzy logic is an intuitive solution to this problem, since the definition of a fuzzy ontology is based on the fuzzy subset theory to precise ontologies in order to represent uncertainties. Moreover, Zhaiet et al. try to define fuzzy ontologies based on the application of fuzzy logic [29], without distinction between precise and fuzzy components. However, Straccia limits itself to defining a fuzzy component from instances [30]. Ghorbel tried to define a fuzzy component based on the integration of uncertainty and imprecision in the definition of a precise component [31]. In the medical context, AlzFuzzyOnto [28] presents a fuzzy ontology specific to Alzheimer's disease (AD). Thus, with the help of experts, the points of uncertainty present in each concept and each relation of the ontology are analysed. Indeed, this ontology allows the generation of fuzzy concepts to represent fuzzy information and data in order to process imprecise knowledge and data and to refine the results obtained [28]. But, to the best of our knowledge, there is no fuzzy ontology in the literature that defines the triage system in ED. Besides, there are several techniques for developing classic ontology [13] but they are not sufficient to construct fuzzy ontologies [14]. Many methods are available to generate fuzzy ontologies such as map fuzzy model [14], FuzzyOntoMethodology [15], FONTO (Fuzzy for ONTOlogy) [17], FOGA (Fuzzy Ontology Generation FrAmework) [16]. The difference between these approaches is mainly in what aspects of the classical ontology are being fuzzified, and these aspects depend on the domain needs. However, the mentioned approaches do not guarantee the encoding of fuzzy in ontologies and the construction of fuzzy case-based domain ontologies at the same time. So, we propose in this paper a novel method which consists in fuzzifying an ontology by ensuring the application of fuzzy subset theory in an automatic way and in defining all the precise and fuzzy domain concepts with the case descriptions. The fuzzification is a process of transforming a precise ontology into a fuzzy ontology in order to model forms of uncertainty [17]. So, in this work, we implement fuzzy ontologies that manage imprecise knowledge and data. We populate the implemented ontology with real data of patients, and we use

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reasoners for semantically querying the resulting fuzzy ontology. The paper has the following contributions:

– the first fuzzy ontology of the triage process to model and reason with medical fuzzy knowledge based on ED patient cases.
– a novel method for developing fuzzy ontology of domain.
– an extension of the ED severity index based on fuzzy concepts to better specify the severity of a patient's case and the possible waiting time.
– the validation of the method on real patient case scenarios.

We conduct this work in the context of a national project called Inter and Intra Hospital Logistics Optimization supported by the National Research Agency (2019-2022).

2 The proposed fuzzy ontology for triage system: FOTS

We propose a fuzzy ontology containing three basics modules: 1) conceptual model, 2) fuzzy-domain model and 3) case and reasoning model. In this section, we present the proposed methodology to develop the fuzzy ontology. Then, we define the novel fuzzy ESI based on fuzzy concepts, named F-ESI_2.0. Finally, we describe the current implemented instance of our proposed ontology based on these three models.

2.1 Proposed methodology for developing fuzzy ontologies: FOntoM

In this paper, we propose the novel FOntoM method in order to meet the needs of medical field which contains very complex vocabulary and knowledge. We drew on the Methontology method [18] adding the FONTO method of fuzzification [17] allowing the definition of the ontology fuzzy concepts. Three main models are created: the conceptual model, the fuzzy domain model and the case and reasoning (Fig.1).

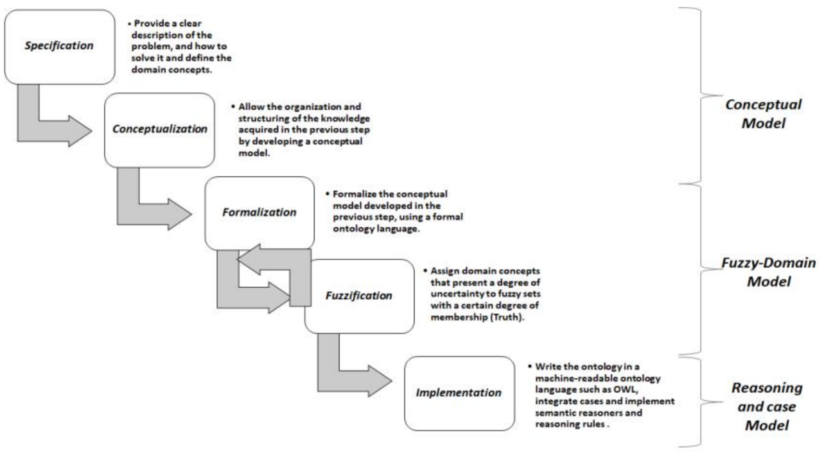

Fig. 1. The FOntoM method

This method is composed of the following steps:

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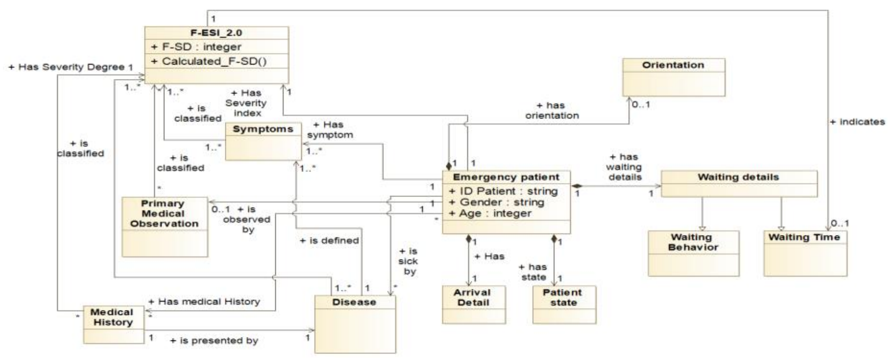
1. Specification to provide a clear description of the target glossary, defining the domain concepts.
2. Conceptualization to allow the organization and structuring of the knowledge acquired in the previous step by developing a conceptual model.
3. Formalization of the conceptual model developed in the previous step, using a formal ontology language.
4. Fuzzification to assign domain concepts that present a degree of uncertainty to fuzzy sets with a certain degree of membership (Truth).
5. Implementation to write the ontology in a machine-readable ontology language such as OWL 2[1]; integrate cases and implement semantic reasoners and reasoning rules.

The proposed ontology FOntoM contains both fuzzy and precise concepts and, as shown in Fig. 1, the specificity of this method is that an iterative loop is made between formalization and fuzzification steps, so the output of this loop is enabled if all the concepts of the fuzzy domain are defined. We choose the FONTO method [17] for fuzzification which is composed of three successive phases: the extraction of the fuzzy concepts, the determination of the fuzzy classes of the ontology and the calculation of the membership degrees. This method allows handling imprecise and vague knowledge through threshold values representing the different possible modalities, ensures quantitative knowledge modeling and codifies ill-defined knowledge. So, the fuzzification process consists in modeling a set of fuzzy concepts basing on the well-known fuzzy logic theory.

2.2 The FOTS implementation process

In this section, we present the FOTS ontology composed of three models: the conceptual model, the fuzzy domain model and the reasoning and case model. The implementation of FOTS is done using the FOntoM method (section 3.1). We detail each model in the following subsections.

The FOTS conceptual model.



[1] https://www.w3.org/TR/owl2-overview/

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Fig. 2. The FOTS generic class diagram

The FOTS fuzzy-domain model.
This This model represents fuzzy domain knowledges according the conceptual model defined in section 3.2.1. We describe our FOTS in OWL 2 Language and develop it in collaboration with the staff of LUHC. The resulting based on our proposed FOTS ontology contains 6 generic classes or concepts: Emergency patient, Disease, F-ESI_2.0 (section 3.3), Primary Medical Observations, Symptoms and Medical History. The root class of these six classes is the Class Thing (table 1).

Table 1. Generic concepts of FOTS fuzzy domain

Generic classes	Description
Emergency patient	all the specific data of a patient such as demographic data, mode of arrival, waiting time and way of waiting.
Disease	patient's illness
F-ESI_2.0	the health state of patient with a fuzzy severity index
Medical Observation	the vital signs observed and revealed by the nurses
Symptoms	patient's symptoms
Medical History	patient's medical history

The OWL 2 classes are performed as sets of individuals (or sets of objects) and the Class Thing represents the set containing all individuals [19]. In this context, the FOTS fuzzy domain contains two levels of knowledge abstraction that we can qualify by knowledge of surface and deep knowledge:

- The generic level: contains the generic concepts of ED domain (Table 1).
- The fuzzy domain level: describes the triage field related to the patient severity defined by FOTS properties and concepts in the next subsection.

The FOTS concepts/properties

To define the domain concepts, we use standard medical ontologies such as SYMP and ICD ontologies to build a medical domain ontology according to the Medical Dictionary of Health[2]. Emergency physicians validate the SD of each element and the relations between classes, then we define all its elements with the OWL 2 language in ontology form. Table 2 presents an overview of the object properties defined in FOTS.

Table 2. The object properties

Object properties	Domain	Range
Has symptoms	Emergency patient	Symptoms
Is sick by	Emergency patient	Disease

[2] https://www.health.harvard.edu/a-through-c

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Has severity index	Emergency patient	F-ESI_2.0
Has defined by	Disease	Symptoms, Vital signs
Has state	Emergency patient	Patient state
Has wait time	Emergency patient	Waiting time

Each property is responsible for defining the relationships between domain concepts in order to create patient case scenarios in the triage process. Therefore, we define uncertain data and inaccurate knowledge in the field of hospital triage by fuzzy concepts and relationships such as medical observations, symptoms and diseases. Each fuzzy concept defines uncertain medical information, and through fuzzy description we can manage this uncertainty and formulate more accurate and correct results. In this context, the logical axioms define concepts by means of logical expressions. The table 3 contains an overview of the axioms defined in the ontology with the mathematical expressions that allow to calculate the membership degree of instances to concepts and fuzzy relations. In order to define fuzzy concepts, three items are created for each of the numerical features: an abstract role (i.e., data property) for the numerical feature, a fuzzy data type for each linguistic term and a fuzzy concrete role (i.e., object property) for each linguistic term. For example, if we consider the variable Peripheral O2 Saturation, it's range of acceptable values would be [0,99], the applicable linguistic terms would be: Very Severe [VSS (0, 86)], Severe [SS (85,86, 91)], Little Tired [LTS (90,91, 95)], and Normal [NS (94, 99)]. First, we create an abstract role named PSatO2. Second, a fuzzy data type is created for each of these fuzzy terms and finally, we have also defined fuzzy concrete roles: hasVSS_PSatO2, hasSS_PSatO2, hasLTS_PSatO2 and hasNS_PSatO2. The previously defined fuzzy datatypes are used as ranges for these roles. As shown in Fig.3, a «Fuzzy Protégé» plugin was used to create the fuzzy datatype VSS_PSatO2.

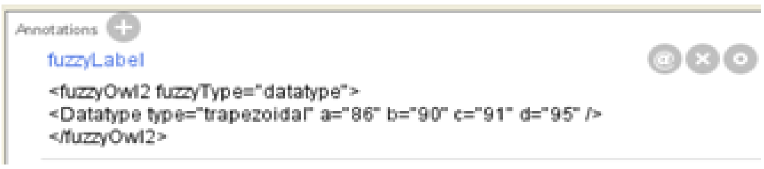

Fig. 3. Fuzzy Datatype Example

Table 4 shows an example of a fuzzy property. This table provides an overview of the reported properties for each non-numeric fuzzy concept. These properties are created in order to define semantic relations and data. In order to exploit these fuzzy concepts in a decision support system and to have adequate results, we define fuzzy reasoners and semantic rules ensuring a detailed description of the real case scenarios. Thus, we define the FOTS reasoning and case model in the following section.

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Table 3. The overview of axioms

Concept Name	Description	Logical Expression
Vital signs	Patient health indicators such as: Systolic blood pressure, heart rate, respiratory frequency, ...	∀ (X), Vital signs (X) ⇒ Systolic Blood pressure (X) ∨ Heart Frequency (X) ∨ Respiratory Frequency (X) ∨ Body Temperature (X) ∨ Pain Level (X) ∨ Electrocardiogram (X) ∨ Glasgow_Score (X) ∨ Peripheral_O2_saturation (X)
Systolic_BP _Normal	Corresponds to the maximum pressure at the time of heart contraction. Its membership function is: SBPN (90, 100, 120, 130)	- SBPN(Value) = 1 if Value ∈ [100 - 120[- SBPN(Value) = (Value - 90) / (100- 90) if Value ∈ [90 – 100 [-SBPN(Value) = (130 - Value) / (130 -120) if Value ∈ [120 - 130 [- SBPN(Value) = 0 else where
Hyper-Systolic_BP	When the maximum pressure at the time of heart contraction is between:] 140 - 180 [membership function is: SBPN (120, 130, 180)	- SBPN(Value) = 1 if Value ∈] 130 –180[- SBPN (Value) = (Value – 120) / (130 –120) if Value ∈ [120 - 130[- SBPN (Value) = 0 elsewhere
Heart frequency_ Normal	Represents the number of heartbeats (or pulses) per unit of time (usually one minute). Its membership function is: FCN (60, 70, 90, 100)	- HFN(Value) =1 if Value ∈ [70 - 90[- HFN (Value) = (Value -60) / (70 - 60) if Value ∈ [60 - 70[- HFN (Value) = (100 - Value) / (100 - Value) / (100 - Value) 90) if Value ∈ [90 - 100] - HFN (Value) = 0 elsewhere

Table 4. The fuzzy property Example

Fuzzy Propriety	Domain	Range	Linguistic term	Syntax of DL	Type FM	FM
Has Systolic_BP_Normal	Emergency patient	Systolic_BP _Normal	Normal	Blood pressure ⊓ ∃ Normal_max.pressure	Trapezoidal	SBPN (90, 100, 120, 130)

The FOTS reasoning and case model.

After creating the fuzzy domain model (previous section), we define the reasoners to transform the model into a functional ontology and to integrate into a decision-support system. This model provides a detailed description for each emergency department patient case scenario containing all medical data. We describe the different relationships between fuzzy and precise medical concepts in our FOTS ontology (section 3.2.2) and set up the case model by defining real patient case scenarios. In fact, Fuzzy DLs are extensions of classical Description Logics (DL) [30]. They have been proposed as languages that can represent and reason on vague or imprecise knowledge [26]. Thus, we use the Fuzzy Dl reasoner to define the severity index of each patient case based on

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the defined concepts. In this context, we apply the fuzzy disjunction rule to define and merge the SD for each symptom and consider the maximum degree in order to find the most accurate index. We use the SWRL (Semantic Web Rule Language) that is a rule language for the semantic web, combining the OWL-DL language and RuleML (Rule Markup Language) to create all possible scenarios of the patient state. These are integrated into the resulting ontology to reason semantically based on rules, for example: "Emergency_Patient (? x) ^ Has_Age (?x, ''very old'')→ Has_Waited_Behavior(?x, ''Valid'')". The exploitation of semantic rules can also be used to process missing data.

The FOTS description.

The resulting ontology contains 108 classes, 50 (fuzzy) object properties, 67 fuzzy datatype properties, 98 fuzzy datatypes, 917 axioms, 750 logical axioms, and 2489 concept instances for the 50 patient cases (Fig. 4). Each object property and each datatype property has an instance for every individual case. The implementation of our fuzzy ontology and specific concept cases is done by the Fuzzy OWL plugin. We have created an object property Has_Part, and its inverse Belongs_To to link all parts of a case to the case description concept Emergency_Patient. We have proposed some axioms to make sure that each case has one concept from each component. In the following section, we use performance measures to evaluate our ontology.

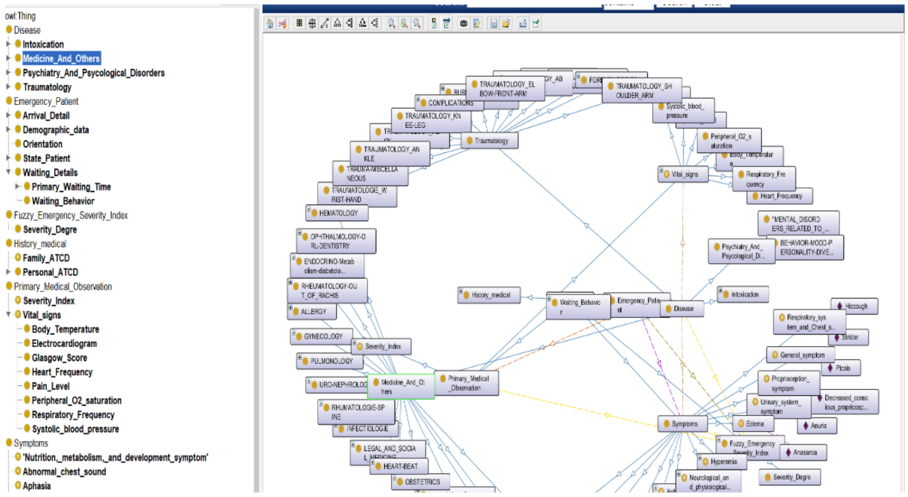

Fig. 4. The FOTS ontology

2.3 The Fuzzy Emergency Severity Index: F-ESI_2.0

The proposed F-ESI_2.0 presents an output of our FOTS ontology and is defined by the fuzzification of the Severity Degree (SD) total of four elements: age, symptoms, medical history and medical observations, which are the primary references for defining a patient's health condition during triage according to health experts. Hence, based on the ESI used nowadays in hospital and in collaboration with the medical staff of the

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ED of Lille University Hospital Center (LUHC), we identified the SD of emergency patient as shown in Table 5.

Table 5. The SD of patient

Severity Degree (SD)/ patient state	Stable state	Moderate state	Urgent state	Very urgent state
SD_{age}	0	1	2	3
$SD_{History\ Medical}$	0	1	2	3
$SD_{Symptoms}$	0	2	4	8
$SD_{Medical\ Observations}$	0	2	4	8

The SD_x defines the SD linked the the x patient health indicator. For example, the SD_{age} defines the SD linked to the patient' age, i.e if the age $\in$[18,40] then SDage=0, if the age $\in$[38, 55] then SDage =1, if the age $\in$[54,76] then SDage=2 and if the age >75 then SDage = 3.

To find the F-ESI_2.0 for each patient, 3 steps are required:

Step 1: Calculate the SD for each item based on existing data.

Step 2: Calculate the sum of the Fuzzy Severity Degree (F-SD).

Step 3: Using the fuzzy concepts, we find the membership degree according to the class found and the corresponding F-ESI_2.0 (Fig.5). In collaboration with health care experts, we select fuzzy classes that present the total F-SD for the elements that influence the patient's condition such as symptoms, age, reason for coming, history and nurses' medical observations. Fuzzy functions are selected according to the fuzzy data interval. Corresponding fuzzy classes are shown in Table 6.

Table 6. The F-ESI_2.0

F-SD	[0, 4[	]2,7[	]5, 10[	]8,13[	>11
F-ESI_2.0	5	4	3	2	1
ESI Level	Nonurgent	Less Urgent	Urgent	Emergent	Resuscitation
Fuzzification Function	Left shoulder function	Trapezoidal function	Trapezoidal function	Trapezoidal function	Right shoulder function

For the calculation of severity regarding symptoms and medical observations, we rely on scientific medical documents that are subsequently validated by emergency physicians and we apply the fuzzy disjunction rules because we have a set of symptoms and vital signs for each patient. Thus, the F-ESI 2.0 can be a powerful tool to measure the severity status of patients, we will be able to evaluate its efficiency by testing it with a triage aid system based on the FOTS ontology but theoretically, this score is better than the existing scores because it is based on fuzzy logic which refines the results. In addition, it takes into account all the medical elements such as medical history which are not considered in the past.

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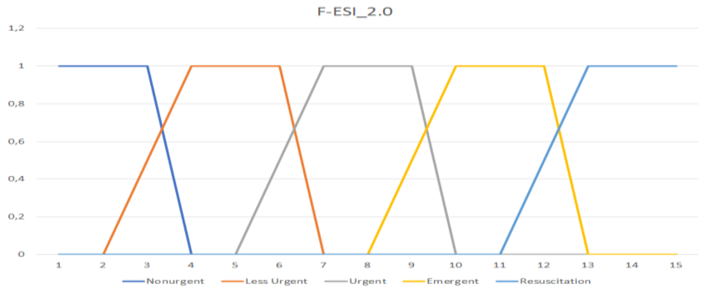

Fig. 5. The membership degree of F-ESI_2.0

3 The FOTS evaluation

The resulting fuzzy ontology is evaluated regarding its syntax, semantics, and content coverage. The evaluation process assesses the conciseness, the correctness, the intelligibility and the adaptability of the ontology. There are no globally accepted evaluation mechanisms [20]. In fact, the ontology must be used, criticized and updated. According to Brewster et al. [21], precision and recall are not suitable for the evaluation because they depend on a comparison between evaluated ontology and a standard one [21]. We follow this method for evaluation.

3.1 Consistency checking

This ontology is serialized in the OWL 2 format with the «Protégé[3]» 4.3 tool. It contains 108 fuzzy classes, 50 fuzzy object properties, 67 fuzzy datatype properties, 98 fuzzy datatypes, and 50 real cases. Consistency checking describes the syntactic-level evaluation. The SWRL rules and Fuzzy DL are developed by the «Protégé» editor to confirm that FOTS is consistent and free of errors. They do not reveal any discrepancies regarding this version of the ontology.

3.2 Criteria of evaluation

There is no benchmark ontology to measure its similarity with our ontology. Moreover, if a gold standard exists, then there will be no need to create other ontologies. But, a comparison with existing ontologies in the same domain is needed. However, there is no fuzzy ontology in the emergency triage to compare with. So, we consider the ontology of El Sappagh et al. [22] for diabetes diagnosis. Several criteria for ontology evaluation quality have been defined [23,24]. We consider also the criteria of Djedidi and Aufaure [23] similar to the work of El Sappagh [22] with several metrics. These criteria concern complexity, cohesion, conceptualization, abstraction, completeness, and comprehension [23] (Table.7). The comparison between our ontology and the Diabetes ontology shows that FOTS is a complete, functional and semantically rich ontology.

[3] https://protege.stanford.edu/

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Table 7. The comparative evaluation table between FOTS and diabetes ontology

Measure		Ontologies	
Criteria	Metrics	The proposed ontology	Diabetes ontology
Complexity	An average number of paths to reach a class from the root.	3	3
	Average number of object properties per class.	1.2	1.3
Abstraction	The average depth of the ontology.	3	2
Cohesion	An average number of connected classes	54	27
Conceptualization	Semantic Richness: Ratio of the total number of semantic relations assigned to classes, divided by the total number of ontology relations (object properties and subsumption relations).	50/50+58= 0.462	58/58+59= 0.495
	Attribute Richness: Ratio of the total number of attributes (data properties describing ontology classes), divided by the total number of ontology classes.	108/67= 1.61	138/62= 2.26
	Average number of subclasses per class.	8	5
Completeness	There are no standard (fuzzy) case base ontologies to compare our ontology with it.	Not Applicable	Not Applicable
Comprehension	Documentation of the properties	5%	2.04%
	Documentation of the classes	97%	88.71%

3.3 Lexical, vocabulary or data level evaluation

Coverage is the completeness of terms or concepts to represent a domain [25]. So, our proposed ontology has to contain concepts and relations equal to those in the domain, and ontology instances identical to instances in the domain. Our ontology actually contains 50 cases, and it is open to other cases insertion. As our ontology has been defined in favor of the emergency triage process, all medical terms used in this medical system exist in the proposed ontology. Moreover, we use the ontologies of standardization such us ICD and SYMP ontology for defining the symptoms and diseases. Thus, the specific glossary of terms for triage are collected from the current system with the help of healthcare workers in LUHC. The coverage of FOTS is tested for all of these terms. FOTS has 100% concept coverage for all medical classes and relations required to describe ED patient cases. All needed concepts and relations to describe ED patient situations have been verified. Finally, the domain experts have evaluated the proposed ontology content regarding the clarity and conciseness. Since all concepts are extracted from the ED database and standardization ontologies, formal definitions are available for all terms. Therefore, FOTS complies with Gruber's three requirements such as clarity, including formal definition of classes, documentation of ontology, and use of classes as required [27].

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3.4 Vagueness evaluation

According to Alexopoulos et .al [25], the evaluation of the vagueness ontology quality has been defined by the set of metrics. These later include:

– Vagueness Spread (VS): In a fuzzy ontology, the concepts, relations, attributes, and data types elements may be of a vague type. The VS measures the extent of vagueness representation in the ontology, and provides an indicator of the ontology's potential comprehensibility and shareability. An ontology with a high value of vagueness spread is less explicit and shareable than an ontology with a low value. As shown in Eq. (1), VS is the ratio of the number of vague ontology elements (classes, relations, and data types), noted by VOE and the total number of elements, noted by OE. We have C (Classes) = 108, OP (Object properties) = 50, FD (Fuzzy Datatypes) = 98, FDP = (Fuzzy Datatype Properties) =67, and FOP (Fuzzy Object Properties) = 12.

$$\mathrm{VS} = \frac{|VOE|}{|OE|} = \frac{FD+FDP+FOP}{C+OP+FD+FDP} = 0.55 \qquad (1)$$

– Vagueness Explicitness (VE): It is the ratio of the number of vague ontological elements that are explicitly identified, noted by EVOE and VOE as in Eq. (2). The higher is the value of this metric, the better is the ontology. All fuzzy elements defined in the proposed ontology are explicitly defined, and fuzzy reasoner (Fuzzy DL) can infer other implicit elements at run time.

$$\mathrm{VE} = \frac{|EVOE|}{|VOE|} = \frac{FD+FDP+FOP}{FOP+FD+FDP} = 1.0 \qquad (2)$$

According to these indicators, we can prove that our ontology presents useful domain knowledge by considering the imprecision and uncertainty of medical information. The fuzzy elements of this domain are well defined explicitly with a very high comprehensibility. These characteristics are very important to put this ontology into a well-functioning decision support system.

4 Conclusion

In this paper, we proposed a novel fuzzy ontology (FOTS) for triage system in ED. The resulting ontology is enriched with multiple types of data, such as fuzzy, precise, text and semantic data. These different types of data facilitate the development of decision support system that contains fuzzy semantic-case retrieval algorithms and support queries expression by nurses. Thus, the FOntoM method allowed us to create a fuzzy ontology with a high coverage of triage domain in emergency services and to define all the useful fuzzy and precise knowledge. The FOTS is the unique fuzzy ontology at the ED and especially in the triage process domain. Moreover, in the evaluation section, we have proven that our functional fuzzy ontology presents triage domain knowledges and considers the imprecision and uncertainty of medical data in defining case scenarios. This representation of uncertainty helps to provide a decision support system with

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high performance and solve the problem of missing data. Therefore, it helps to improve triage and quality of care in the ED. In future work, we will study semantic retrieval algorithms that can be a potential solution for improving the integration of the ontology and solving the incompleteness of the annotations at querying time. Thus, we will focus to enhance the implementation of our ontology by using a programming language. The goal is to facilitate data retrieval and by setting up our ontology with the existing triage system. This will make it possible to add case-based reasoning and machine learning tools to improve the precision of our decision system.

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