MEDINFO 2021: One World, One Health – Global Partnership for Digital Innovation
P. Otero et al. (Eds.)

doi:10.3233/SHTI220220

Ontology for Overcrowding Management in Emergency Department

Khouloud Fakhfakh Maala[ab], Sarah Ben-Othman[a], Laetitia Jourdan[a], Grégoire Smith[c], Jean-Marie Renard[bc], Slim Hammadi[a] and Hayfa Zgaya Biau[ab]

[a] Centre de Recherche en Informatique Signal et Automatique de Lille, CRIStAL, UMR 9189, Central Lille, F-59000 Lille, France,
[b] Cerim, University of lille, Lille, France
[c] LUHC Lille, Lille, France

Abstract

Emergency department (ED) overcrowding is an ongoing problem worldwide. Scoring systems are available for the detection of this problem. This study aims to combine a model that allows the detection and management of overcrowding. Therefore, it is crucial to implement a system that can reason model, rank ED resources and ED performance indicators based on environmental factors. Thus, we propose in this paper a new domain ontology (EDOMO) based on a new overcrowding estimation score (OES) to detect critical situations, specify the level of overcrowding and propose solutions to deal with these situations. Our approach is based on a real database created during more than four years from the Lille University Hospital Center (LUHC) in France. The resulting ontology is capable of modeling complete domain knowledge to enable semantic reasoning based on SWRL rules. The evaluation results show that the EDOMO is complete that can enhance the functioning of the ED.

Keywords:

Emergency Departments, Domain Ontology, Overcrowding management

Introduction

Emergency department overcrowding is a main problem faced by hospitals in France and in developed countries. The management of patient flows, in particular recurrent flows and flows following health crises (influenza, heat wave, exceptional situations) is one of the most important problems that EDs face. To manage this influx of patients, emergency departments need significant human and material resources, as well as a high degree of coordination between these resources. Under these conditions, medical staff is frequently confronted with overcrowding situations that greatly complicate their task and cause stress. Indeed, an emergency is a situation that involves a critical risk to property, life, health or the environment. In emergency scenarios, sharing knowledge and information about emergencies and affected entities (people, infrastructure) is essential to improve safety and infrastructure [1]. Knowledge management (KM) is responsible for determining what information is needed to recover from a critical situation. Improving the effectiveness of KM can not only help decision makers make faster and better decisions, but also enable various organizations to share and reuse different resources. The main element of the decision support system is the knowledge which can influence and guide the decisions made. This is the main key to the success of real-time decision making [2]. Ontology engineering has become a useful and popular technology in computer science and knowledge science [3]. Ontology is a form of conceptualization of real-world scenarios. It has been applied to decision support systems (DSS) to provide a formal representation of knowledge. It can improve interaction and coordination between different emergency organizations. The domain ontology for emergency management is a mechanism to provide a consistent view of the specific domain that can be used by all relevant authorities. Semantic technology has been used to build an extensible data model (the Resource Description Framework, RDF), in which data is represented as meaningful triples (subject, predicate, and object) [17]. The ontology is used to create the knowledge base that stores facts and procedures about the emergency and expert advice. A major aspect of this paper is to define a knowledge representation structure in the form of an ontology that provides information about emergency situations. These are essential to achieve a successful resolution of an evolving situation and to propose adequate solutions according to the severity of the solution. The ontology thus created will be able to represent and capture enough information about situations such as natural disasters, accidents, pandemics and climate data that can influence the demand flows on emergencies. It is a hierarchical model that forms true and faithful representations, so that queries of the model yield reliable results. This hierarchical contingency model indicates the classification of situations and the relationship between situational elements at different levels of granularity. Making quick decisions in the chaos of emergency situations is a very difficult task. The process can become difficult when a decision takes into account several internal and external factors and resources. Before drawing any conclusions or assisting in decision making, the medical staff must be aware of the resources needed and the resources available at a given time. In this context, we propose an ED Overcrowding Management (EDOMO) domain ontology to establish the overcrowding management process and propose solutions for each situation. In addition, determining the level of overcrowding in the ED is crucial to avoid undesirable outcomes. If the level of overcrowding is currently measured, overcrowding plans can be created. Various assessment systems have been developed to detect ED overcrowding. These include real-time analysis of ED demand indicators, the ED Work Index, the National ED Overcrowding Study (NEDOCS), and ED overcrowding rating systems [4]. Among these scoring systems, NEDOCS has shown good results [5]. However, in another study [6], NEDOCS showed limitations due to not taking into account important real-time factors, such as current ED load and climatic factors. For this purpose, we propose a new overcrowding estimation score (OES) to assess the ED situation by considering all external factors and ED resources. We conduct this work as part of a national project entitled Inter- and intra-hospital logistics optimization supported by the National Research Agency (2019-2022).

Methods

Emergency Department Overcrowding Management Ontology (EDOMO)

In this section, we propose the EDOMO ontology for owercowding management in ED. The ontology is based on an overcrowding estimation score (OES) to evaluate crowding situations in EDs. The implementation of EDOMO is done using the methontology method. We detail each part in the following subsections.

Ontology development methodology

Knowledge engineering is responsible for "ontology modeling" to identify the representation of primitives and meanings that will be used for formal knowledge modeling [7]. Various methodologies for ontology development exist in the literature [8], such us METHONTOLOGY, SENSUS, TOVE, IDEF5 and the seven-step method. Ontology construction is an iterative process. It is very important to choose the right methodology for the new ontology. In this paper, we adopte Methontology methodology [8] to create the domain ontology because it not only has detailed technical support and advantages in model creation, but also has advantages in the detailed modeling process to build the ontology model in the medical domain. This method is composed of the following steps:

1. Specification to deliver a clear description of the target vocabulary, identifying the domain concepts.
2. Conceptualization to enable the organization and structuring of the knowledge acquired in the first step by creating a conceptual model.
3. Formalization of the conceptual model developed in the previous step and of the entire domain glossary built, using a formal ontological language.
4. Implementation to build the ontology in a machine-readable ontology language such as OWL 2 with an ontology development tool; and integrate case scenarios and implement semantic reasoners.

This method can be useful to formalize a multi-model ontology which will presented in the following section.

The EDOMO ontology models

The EDOMO ontology is composed of three models: the Domain model, the case model and the reasoning model.

The Domain model :

The result of our proposed EDOMO ontology contains a single generic concept which is the situation and six main subclasses which define the different situations of ED: Patients, Causes, Overcrowding classes, Context, Solution and Evaluation. The root class of these classes is the Thing class (Table 1).

Table 1– Main concepts of EDOMO domain

Classes	Description
Situation	presents the generic class of the ontology and defines the scenarios of different crowding or normal situations in the ED
Causes	defines the factors that can cause overcrowding situations in the ED
Patients	presents specific data on ED patients
Overcrowding classes	classifies the different situations according to their level of overcrowding
Solution	proposes instant solutions to help health care personnel manage these situations.
Evaluation	allows the exact evaluation of a situation at a given time according to well-defined performance indicators.
Context	defines the internal and external environment of the ED.

OWL 2 classes are realized as sets of individuals (or sets of objects) and the class Thing represents the set containing all individuals [9]. In this context, the EDOMO domain contains two levels of knowledge abstraction that we can qualify by knowledge of surface and deep knowledge:

- The generic level: contains the main concepts of overcrowding situation domain in the ED (Table 1).
- The domain level: describes the ED environment field that influences crowding situations in EDs, defined by EDOMO properties and concepts.

To define the domain concepts, we use standard medical Dictionary of ED and Medical Dictionary of Health in collaboration with the staff of LUHC to build a healthcare domain ontology. Emergency physicians have validated the EDOMO ontology and each element defined and the relations between classes, then we describe all its elements with the OWL 2 language in ontology form. Table 2 presents an overview of the properties defined in EDOMO.

Table 2– The EDOMO properties

EDOMO Properties	Types	Domain	Ranges
has_performance_indicator	Object property	Situation	Performance indicators
is_defined_by	Object property	Overcrowding_classes	Overcrowding_screre
is_evaluated_by	Object property	Situation	Evaluation
has_temperature	Data property	temperature	float
has_patient_ admitted number	Data property	Patients_admitted	int
has_doctors_ number	Data property	Doctors	int

Each property is responsible for defining the relationships between domain concepts in order to create overcrowding situation case scenarios in the ED. Therefore, we define the different data and knowledge in the field of ED by domain concepts and relationships such as context, evaluation and patients. This ontology presents a combination of exact indicators such as the ED capacity at time t and estimated indicators such as the climate forecast. Each domain concept defines information that can influence the ED environment.

The case model:

Based on the FOTS ontology [10], we developed the EDOMO ontology that represents the ED environment and overcrowding situations. EDOMO provides a case model. The latter presents a detailed description for each ED overcrowding situation scenario containing all data. We describe the different relationships between domain concepts in our EDOMO ontology and set up the case model by defining real ED situation case scenarios. To improve the communication between the case model and the domain model, we integrate these situation cases into the ontology through the data and object properties (Figure 1).

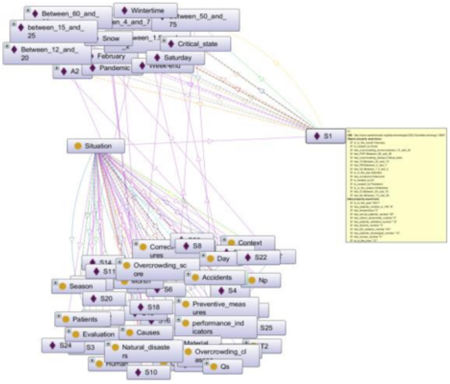

Figure 1– EDOMO case model

The reasonning model:

After creating the domain model and the case model, we define the reasonning model to realize a functional ontology and to integrate into a decision-support system. 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 ED situations. These are integrated into the resulting ontology to reason semantically based on rules, for example:

EDOMO:Situation(?S) ^ EDOMO:Overcrowding_score (?Y) ^ EDOMO:is_evaluated_by (?S,?Y) ^ swrlb:lessThanOrEqual (?Y, "25"^^xsd:long) ^ swrlb:greaterThanOrEqual (?Y, "15"^^xsd:long) -> EDOMO:Overcrowding_classes (EDOMO:Critical_state)

In addition, this model provides rules that assess overcrowding situations and manage these situations by proposing solutions to help healthcare workers. Thus, each rule is described with the properties and instances defined in the ontology. It is based on performance indicators to give an accurate assessment. The defined rule base has been validated by the medical staff of LUHC. The exploitation of semantic rules can also be used to manage missing data.

EDOMO based on overcrowding management process

The overcrowding management process is composed of three steps:

-identify the performance indicators and calculate the overcrowding estimation score (OES).

-Classify the ED situations into four states: normal state, degraded state, critical state and very critical state.

-Propose adequate actions to manage the different levels of overcrowding.

ED performance indicators

The measurable performance indicators that we have selected and validated with the medical staff of the Adult Emergency Department (AED) of Lille and based on the work of Kadri [11] are:

1. PWT: waiting time between the hostess taking charge (T_e) and the first medical examination (T_c).

$$PWT = T_e - T_c \tag{1}$$

2. T2: waiting time from the hostess (T_e) to the nursing consultation (T_{nc}) (Equation 2).

$$T_2 = T_e - T_{nc} \tag{2}$$

3. N_p: number of patients present at the AED when a new patient arrives

4. PM: ratio of the number of patients present at the AED to the number of doctors (N_d) potentially available (Equation 3): As the number of physicians changes according to the period of the day, PM is updated at each period variation.

$$PM = \frac{N_p}{N_d} \tag{3}$$

5. Q_S: ratio of the actual stay time in the hospital of a patient in non-emergency state LOSactual, and the theoretical stay time LOSth (Equation 4). The LOSth in the hospital is 210 minutes.

$$Q_s = \frac{LOSactual}{LOSth} \tag{4}$$

6. C_t: the percentage of the current load at time t. It is the ratio of the number of patients present in the ED and its maximum capacity (N), taking into account the inflow and outflow (Equation 5).

$$C_t = \frac{N_e + N_a - N_s}{N} * 100 \tag{5}$$

Where N_a is the number of patients arriving at the ED, N_e is the patients number in ED and N_s is the number of patients discharged at time t.

The threshold values for each situation class are presented in the following table 3:

Table 3– The threshold values of Performance indicators

Performance indicators	EDA State			
	Normal	Degraded	Critical	Very critical
PWT	PWT< 60	60<PWT< 90	90<PWT< 180	PWT>180
T2	T2<25	25<T2<50	50<T2<70	T2>70
Np	Np<12	12<Np<20	20<Np<40	Np>40
PM	PM<4	4<PM<7	7<PM<10	PM>10
Qs	Qs<0.8	0.8<Qs< 1.5	1.5<Qs<2	Qs>2
Ct	Ct<50	50<Ct<75	75<Ct< 120	Ct>120

Overcrowding Estimation Score (OES)

The OES is proposed to accurately assess the level of crowding in the ED. This score is computed based on the performance indicators mentioned in the previous section (Equation 6). These indicators are selected in collaboration with emergency specialists.

$$OES = \sum_{1}^{K} RS_K \tag{6}$$

Where k is the number of performance indicators.

Table 4– The OES score

	EDA State			
	Normal	Degraded	Critical	Very critical
(RS_k)	1	2	4	5
OES	[0,7]	[8, 14]	[15, 25]	[26, 30]

To calculate OES, firstly, we identify the risque score (RS_k) for each performance indicator (Table 3) according to Table 4 and then we apply equation (6). The RS_k is given for each performance indicator according to its ED state.

OES is created using the SWRL rules in order to integrate it into the EDOMO ontology as follows :

EDOMO:Situation(?H) ^ EDOMO:PM(?X) ^ EDOMO:has_risk_score(?X, ?t) ^ EDOMO:Ct(?Y) ^ EDOMO:has_risk_score(?Y, ?S) ^ EDOMO:Np(?N) ^ EDOMO:has_risk_score(?N, ?M) ^ EDOMO:PWT(?F) ^ EDOMO:has_risk_score(?F, ?D) ^ EDOMO:Qs(?R) ^ EDOMO:has_risk_score(?R, ?C) ^ EDOMO:T2(?P) ^ EDOMO:has_risk_score(?P, ?B) ^ swrlb:add(?Z, ?t, ?S, ?M, ?D, ?C, ?B) -> EDOMO:Overcrowding_score(?Z) ^ EDOMO:has_overcrowding_score(?H, ?Z).

Overcrowding management actions

Based on Kadri's work [11] and in collaboration with the health specialists, we selected the following actions according to two categories which are patient flows and resources according to the level of overcrowding specified in the previous step :

Actions on the care load flow (patient flow):

- Incoming patient flow: Decrease of incoming patients (call the EMS[1] to refer patients to other emergency structures).
- Patient flows admitted to the ED: apply priority rules to better manage patient flow in the ED to limit waiting times and length of stay, transfer patients from the STHU[2] to other departments and adjust the care provided to patients. These rules can be defined according to different criteria: type of patient, length of stay, progress of care, combination of one or more of the above criteria.

Actions on resources:

- Human resources: add doctors or nurses depending on availability in other departments.
- Material resources: transform one or two STHU rooms into consultation room.

Each action is described in the EDOMO ontology via the SWRL rules by proposing for each scenario an overcrowding situation.

Results

To implement the EDOMO domain ontology, we used Protégé 5.5 (Figure 2). It is an open source software [12] that provides a plug-and-play environment for rapid application development. Protégé is the most familiar tool for developing the ontology. Developers can create the ontology easily through its graphical interface without having to worry about the syntax language. Thus we integrate the SWRLTAB tool into protégé for the creation and exploitation of SWRL rules. Thus, we have selected 100 overcrowding scenarios from a real database of the ED in LUHC hospital and we implemented our ontological base in EDOMO. It is a 4-year database including arrival information between 2016 and 2020. This work is part of the OIILH project (2018-2022): Optimization for inter and intra logistics in hospitals. This project is supported by the French research agency and referenced by ANR-18-CE19-0019. The resulting ontology contains 50 classes, 25 object properties, 15 data properties, 687 axioms, 546 logical axioms, and 251 concept instances for the 100 overcrowding situations. Each object property and each data property has an instance for every situation case.

Figure 2– EDOMO ontology structure

In addition, the SWRL rules that are created by the SWRLTAB and Protégé tools, are generated with the JESS inference engine. The rule base contains 50 semantic rules (Figure 3).

Figure 3– SWRL Rules implementation

Discussion

Ontology evaluation requires formal and appropriate evaluation criteria. Therefore, it is essential to select and apply appropriate evaluation approaches that are suitable for the given domain ontology. In the following subsection, we review the different evaluation approaches that have been applied to EDOMO in order to evaluate it. There is no gold standard ontology to measure its similarity to our ontology. But, a comparison with existing ontologies in the same domain is necessary. Thus, we consider the Diabetes ontology (DO) [13] for diabetes disease diagnosis. Several criteria for evaluating the quality of ontologies have been defined [14,15]. We also consider the criteria of Djedidi and Aufaure with several metrics. These criteria concern complexity, cohesion, conceptualization, abstraction, completeness and comprehension [14] (Table 5). The comparison between our ontology and the DO shows that EDOMO is a complete, functional and semantically rich ontology. Based on the above criteria, table 5 presents a comparison between the EDOMO and the DO ontology. These indicators presented in this comparison (table 5) assess the reasoning, consistency and applicability of the ontology. According to these indicators, we can prove that our ontology presents useful practical knowledge

[1] Emergency Medical Service

[2] Short-term hospitalization unit

considering the vagueness and uncertainty of medical information. These features are very important to put this ontology into a well-functioning DSS.

Table 5– The comparative evaluation table between DO and ESMO ontology

Criteria	Metrics	DO	EDO MO
Complexity	The average number of paths to reach a class starting from the root.	3	6
	The average number of object properties per class.	1.3	4.1
Abstraction	The average depth of the ontology.	2	3
Cohesion	The average number of connected classes	27	46
Conceptualization	Semantic Richness: Ratio of the total number of semantic relations assigned to classes, divided by the total number of relations in the ontology (properties and subsumption relations).	58/58+ 59= 0.495	25/25+ 15= 0.625
	Attribute Richness: Ratio of the total number of attributes (data properties) divided by the total number of classes in the ontology.	138/62 =2.265	215/40 = 5.37
	Average number of subclasses per class.	5	4
Completeness	There are no standard ED situation ontologies to compare our ontology to.	Not Applicable	Not Applicable
Comprehension	Documentation of the properties	2.04%	7.04%
	Documentation of the classes	88.71	93.71

Conclusions

In this paper, we propose a new complete ED domain ontology (EDOMO) to handle the overcrowding in EDs. This ontology is enriched with several types of data (e.g textual and semantic data) which facilitate the development of a DSS. This latter contains semantic reasoning algorithms through SWRL rules to assess the situations of EDs and propose health care personnel to manage them. Thus, the overcrowding estimation score (OES) corresponds to a semantically ontology-based assessment tool with a high coverage of the ED domain and its environment by defining all the useful knowledge. We prove in this paper that our functional ontology presents the necessary knowledge of the emergency domain and can be integrated into a DSS based on semantic reasoning. This allows us to provide very efficient results and to solve the problem of missing data. Thus, this model can make an efficient combination between real and estimation data based on semantic reasoning. Therefore, it can improve the quality of emergency care and help health care workers in critical situations. In future works, we can improve the OES by using fuzzy logic. In addition, we will propose a machine learning algorithm that can be a potential solution to improve the accuracy of the estimated data in order to decrease the uncertainty. Also, it is crucial to test the new score in real time environment and integrate the remainning load as proposed in [16], we will focus on improving the implementation of our ontology using a the current ED system in use. This will allow us to add case-based reasoning and machine learning tools to improve the accuracy of our decision system.

References

[1] Othman, S. H., & Beydoun, G. (2013). Model-driven disaster management. Information & Management, 50(5), 218-228.

[2] Jain, S., Mehla, S., & Agarwal, A. G. (2018, July). An ontology based earthquake recommendation system. In International Conference on Advanced Informatics for Computing Research (pp. 331-340). Springer, Singapore.

[3] Jain, S., Mehla, S., & Wagner, J. (2021). Ontology-supported rule-based reasoning for emergency management. In Web Semantics (pp. 117-128). Academic Press.

[4] Jones, S. S., Allen, T. L., Flottemesch, T. J., & Welch, S. J. (2006). An independent evaluation of four quantitative emergency department crowding scales. Academic Emergency Medicine, 13(11), 1204-1211.

[5] Ahalt, V., Argon, N. T., Ziya, S., Strickler, J., & Mehrotra, A. (2018). Comparison of emergency department crowding scores: a discrete-event simulation approach. Health care management science, 21(1), 144-155.

[6] Ilhan, B., Kunt, M. M., Damarsoy, F. F., Demir, M. C., & Aksu, N. M. (2020). NEDOCS: is it really useful for detecting emergency department overcrowding today?. Medicine, 99(28).

[7] Sadiche, Y. N. (2008). Profil Utilisateur d'une PLATEFORME E-Learning. Mémoire de fin d'études pour l'obtention du diplôme d'ingénieur d'état en informatique à l'Institut National de Formation en Informatique.

[8] Fernández-López, M., Gómez-Pérez, A., & Juristo, N. (1997). Methontology: from ontological art towards ontological engineering.

[9] Abeysiriwardana, P. C., & Kodituwakku, S. R. (2012). Ontology based information extraction for disease intelligence. arXiv preprint arXiv:1211.3497.

[10] Fakhfakh, K., Othman, S. B., Jourdan, L., Smith, G., Renard, J. M., Hammadi, S., & Zgaya-Biau, H. (2021). Fuzzy Ontology for Patient Emergency Department Triage. In International Conference on Computational Science (pp. 719-734). Springer, Cham.

[11] Kadri, F., Chaabane, S., & Tahon, C. (2014). A simulation-based decision support system to prevent and predict strain situations in emergency department systems. Simulation Modelling Practice and Theory, 42, 32-52.

[12] Liu, Y., Chen, S., & Wang, Y. (2014). SOFERS: Scenario ontology for emergency response system. Journal of Networks, 9(9), 2529.

[13] El-Sappagh, S., & Elmogy, M. (2017). A fuzzy ontology modeling for case base knowledge in diabetes mellitus domain. Engineering science and technology, an international journal, 20(3), 1025-1040.

[14] Djedidi, R., & Aufaure, M. A. (2010, February). ONTO-EVO A L an ontology evolution approach guided by pattern modeling and quality evaluation. In International Symposium on Foundations of Information and Knowledge Systems (pp. 286-305). Springer, Berlin, Heidelberg.

[15] Yu, J., Thom, J. A., & Tam, A. (2005). Evaluating ontology criteria for requirements in a geographic travel domain. In OTM Confederated International Conferences" On the Move to Meaningful Internet Systems" (pp. 1517-1534). Springer, Berlin, Heidelberg.

[16] Chandoul, W., Hammadi, S., Camus, H., Zgaya, H., Di Pompeo, C., & Trincaretto, F. (2012). Evolutionary approach for multi-objective scheduling in surgical unit. In Conférence francophone gestion et ingénierie des systèmes hospitaliers (GISEH 2012).

[17] Gruber, T. R. (1991). The role of common ontology in achieving sharable, reusable knowledge bases. Kr, 91, 601-602.