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Discovering frequent patterns for in-flight incidents

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Abstract

Objectives: In order to get a clearer idea of in-flight medical emergencies management, the application of Data mining tools can be useful to facilitate knowledge discovery from data collected by existing studies. The objective of this work is to conceptualize the construction of a Clinical Decision Support System (CDSS) in three stages corresponding to the representation levels necessary to extract knowledge from information and raw data.

Method: The method can be summarized in three parts: (1) in-flight medical incident data search, (2) the validation of this data using Data mining tools, (3) the construction of the CDSS in 3 steps corresponding to the levels of knowledge representation. These three steps will be carried out using tools such as EORCA (Event Oriented Representation for Collaborative Activities) which includes action codification with regard to an ontology and event representation.

Result: Data processing services provide a good structuration for information about in-flight medical incidents from which useful knowledge can be generated could improve the handling of other incidents by adapting the medical emergency equipments, for example. This structuring can be facilitated by the use of CDSS to fill in any gaps, increase coherency, and provide decision makers with a more complete picture of options that might be involved in a critical situation.

Conclusion: We proposed an evolving framework facilitating the description of in-flight medical emergencies with adequate data collection and appropriate information that are required for producing interesting rules and better decisions. The data collected nourishes the organization of information, which can be improved over time by continuous integration of evidence gained from the number of incidents treated. Finally, it is proposed to strengthen requirements concerning the medical equipments available on-board, particularly in the light of knowledge resulting from the selection and approval of interesting rules.

Keywords: Data mining; Association rule; Ontology reasoning; Decision system; Air transport

1. Introduction

While airline companies yearly carry about three billion people (Peterson et al., 2013; Naouri et al., 2016), commercial airplanes are still places where medical coverage is not optimal. This large increase in passengers have naturally increase the number of medical incidents and the management of these incidents have become a crucial problem. Even if there is a lot of work reporting these incidents, the exploitation of data to improve the management is very difficult. This is due to several factors among others, the lack of a common administrative and legal framework to harmonize the management of these incidents, and the lack

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of appropriate tools for collecting and structuring this data. In the work described in this document, we will focus on this last point in order to facilitate the preprocessing phase of data mining. The efforts put during the preprocessing phase have a considerable impact on the subsequent data mining and post preprocessing phases, then this can require great time and cost.

Therefore, the preprocessing phase is essential in the process of extracting knowledge from the data and requires significant attention in order to have reliable data before the extraction algorithms are applied, thus, guaranteeing to a certain extent the quality of the obtained results. There may be different difficulties in exploiting the databases available for knowledge extraction. These difficulties stem from the fact that real-world databases are generally dynamic, incomplete and noisy, with an increasing number of raw data. Other concerns are whether the database contains adequate and relevant information for the operation. The most prominent data preprocessing algorithms cover missing values imputation, noise filtering, dimensionality reductions (including features selection and space transformations), instance reduction (including selection and generation), discretization and treatment of data for imbalanced preprocessing (García, Ramírez-Gallego, Luengo, Benítez, & Herrera, 2016). These techniques are important to improve the quality of the data available for further data mining algorithms, and they provide strong foundational elements for formal reasoning and knowledge generation. Furthermore, in principle, this is a reasonable way to understand the properties of the data, to delete the unattractive data, to enrich the data with additional information, to split or create new attributes, and/or to combine them in order to improve their consistency and relevance. Hence, advantages of preprocessing techniques include, among others, a faster and more precise learning process, and more comprehensible structure of raw data with a reduction of the complexity inherent to real-world datasets, so that they can be effortlessly processed by target data mining solutions (Ramírez-Gallego, Krawczyk, García, Woźniak, & Herrera, 2017).

The purpose of this paper is to extract interesting knowledge from databases describing in-flight medical incidents. In order to obtain coherent and understandable association rules from the used databases, there is need to apply some preprocessing procedures that can facilitate the collection and organization of data concerning these aeronautical incidents. As reported by Hinkelbein et al. (2014), there are more and more in-flight medical incidents but valid data on their causes and consequences are rare. This is due to the fact that, many incidents are not documented and if so, it is not done properly. In addition, there is a lack of standardization of in-flight medical incident management. This does not facilitate the correct understanding of the passenger health model, which is needed to adapt the medical emergency equipment of each target flight. The adopted preprocessing phase includes a semantic enrichment process using an ontological representation for the description of in-flight medical incidents. Then, an association rule mining method is applied for discovering interesting relations between variables in the studied databases.

The rest of the paper is organized into five sections: Section 2 provides a background of the state-of-the-art about description of in-flight medical incidents. Section 3 presents the used method for knowledge discovery from data-base including preprocessing (feature selection), data mining (frequent patterns and association rules) and post processing (ontology reasoning). In Section 4, the result and discussion is described at conceptual, logical and implementation level. The conclusion is presented in Section 5 with particular emphasis on the contribution of the paper and possible future works.

2. State of the art

Ideally, the airline industry should be conducive to the documentation of aeronautical incidents (e.g. concerning humans or materials) with relevant data. This storage of incident data should constitute a pivotal resource from which the medical aviation community can elaborate some integrated and efficient strategies to develop an increased understanding of inflight emergencies. Besides, the databases of medical in-flight incidents must be accessible to the general public, and the associated information must meet certain criteria of clarity to ensure that it is intelligible; since this can allow passengers understanding of airlines medical guidelines and medical clearance processes.

In order to understand the environment of medical incidents, it is useful to examine data collected from the various existing studies (Costa, 2015; Peterson et al., 2013; Mahony, Myers, Larsen, Powell, & Griffiths, 2011). The aim of this work is to use a data mining method with a domain ontology to find all the important information related to the management of medical incidents in the airplane. Specifically, it may be indispensable to look for correlations between the characteristics of the passengers involved in air accidents, the care of these passengers and the results of this care (diversion, admission to the hospital, use of resources, etc.).

Thus, considering the limitations, opportunities, and requirements described by the state of the art of medical incidents in the airplane, we proposed a system that fits into the management of in-flight medical incidents.

The following table (Table 1) shows a set of works cited and their characteristics. It gives an overview of the problems raised in the management of in-flight medical incidents.

The literature (described in Table 1) shows that medical incidents had been happening long before that but there are diverse themes related to their description and management (adequacy of medical resources (Hinkelbein et al., 2014; Hinkelbein, Neuhaus, Böhm, Kalina, & Braunecker, 2017; Costa, 2015; Naouri et al., 2016), medico legal issues (Peterson et al., 2013; Costa, 2015; Bukowski & Richards,

Table 1
Themes reported by existing works.

Themes	Articles
Data collection	Mahony et al. (2011), Peterson et al. (2013), and Costa (2015)
Reviews	Smith (2008), Hinkelbein et al. (2013), and Naouri et al. (2016)
Methods to manage incidents	Mahony et al. (2011), Peterson et al. (2013), Costa (2015), and Naouri et al. (2016)
Adequacy of medical resources	Hinkelbein et al. (2014), Hinkelbein et al. (2017), Costa (2015), and Naouri et al. (2016)
Medico legal issues	Peterson et al. (2013), Costa (2015), and Bukowski and Richards (2016)

2016), etc.). Researchers are watching at diverse ways of categorizing these medical incidents, as it concerns either number of flights or number of passengers. There is no debating that emergencies do occur but the actual numbers of emergencies are vague for several reasons including the absence of an international registry of in-flight medical incidents/emergencies and the lack of communication between various reporting systems are available in parallel. Commercial airlines handle their incidents in a very general range of ways but, there are some common characteristics among most of them, one of which is the use of medical kits. These kits vary from basic (e.g. Adhesive Bandage compresses and Antiseptic Swabs) to robust (e.g. AED's (Automated External Defibrillators)) depending on the airline and the distance (Mahony et al., 2011; Peterson et al., 2013; Costa, 2015; Naouri et al., 2016).

Furthermore, some indications from the medical aviation community suggest that most medical emergencies are related to pre-existing conditions, meaning, these critical events do not solely depend of aeronautical factors but also vary according to some underlying vulnerabilities of passengers (Smith, 2008; Hinkelbein, Spelten, Wetsch, Schier, & Neuhaus, 2013; Naouri et al., 2016). These medical vulnerabilities can be associated to risk factors that are unknown or improperly managed by the primary care providers (Mahony et al., 2011; Peterson et al., 2013), (Costa, 2015). It's essential to have much more preventive actions targeted at the population who are medically vulnerable and do not take the suitable precautions before they could fly on commercial airlines.

In the considered context, data mining techniques can be useful to reach out the most common diseases in cases of aeronautical emergencies occurring in commercial airline flights. Specifically, association rule mining can be engaged to discover interesting rules (according to the probabilities of patterns) in a set of incidents from the target database. The use of such data mining techniques should be helpful to obtain useable information by the discovery of existent association rules between these incidents and to start exploring opportunities for knowledge creation and decision-making support.

In the next section, we describe the proposed method for knowledge discovery from databases. This method comprises the following steps: (i) preprocessing (e.g. feature selection and codification), (ii) data mining (e.g. association rule mining), and (iii) post processing (e.g. knowledge integration with ontology reasoning).

3. Method

The adopted method is inspired by the EORCA (Event Oriented Representation for Collaborative Activities) (Pellegrin et al., 2005; Pellegrin, Gaudin, Bonnardel, & Chaudet, 2010), that is a method for observing and formalizing the activities of health professionals during collaborative medical care. EORCA is based on three steps aimed at facilitating codification of information and representation of knowledge resulting from collaborative medical activities (Figs. 1 and 2):

- An observation step that produces an accurate description of natural language of patients' care scenario.
- A second step extracts events' components and sequencing from the description of care scenario.
- A third step provides an algorithm representing the sequences of medical care.

There are three categories of databases in which are reported medical events from commercial airlines: (i) medical events with calls to the contracted medical service provider, (ii) medical events where the locked medical kit was opened, and (iii) medical events reported in an electronic log system by chief pilot and flight attendants. The proposed method (Fig. 2) for knowledge discovery from database comprises three main phases: (i) preprocessing with feature selection and codification, (ii) data mining with association rule mining, and (iii) post processing with ontology reasoning.

3.1. Preprocessing for identification of In-flight Medical Incidents (IMI)

Data preprocessing implicates transforming raw data into an understandable format. Real-word data is habitually incomplete, inconsistent, and/or lacking in certain actions or tendencies, and is likely to hold many errors. Data preprocessing arranges raw data for advance processing. Data preprocessing comprises the following tasks:

- data cleaning: it can be applied to fill in missing values, smooth noisy data, identity or remove outliers, and remove inconsistencies.
- data integration: it consists to merge data from multiple sources into a coherent data store, such as a data warehouse.
- data transformation: the techniques such normalization and aggregation may be applied.
- data reduction: it permits to reduce representation in volume but produces the same or similar analytical results (e.g. the data size is reduced by aggregating, eliminating redundant features, or clustering)

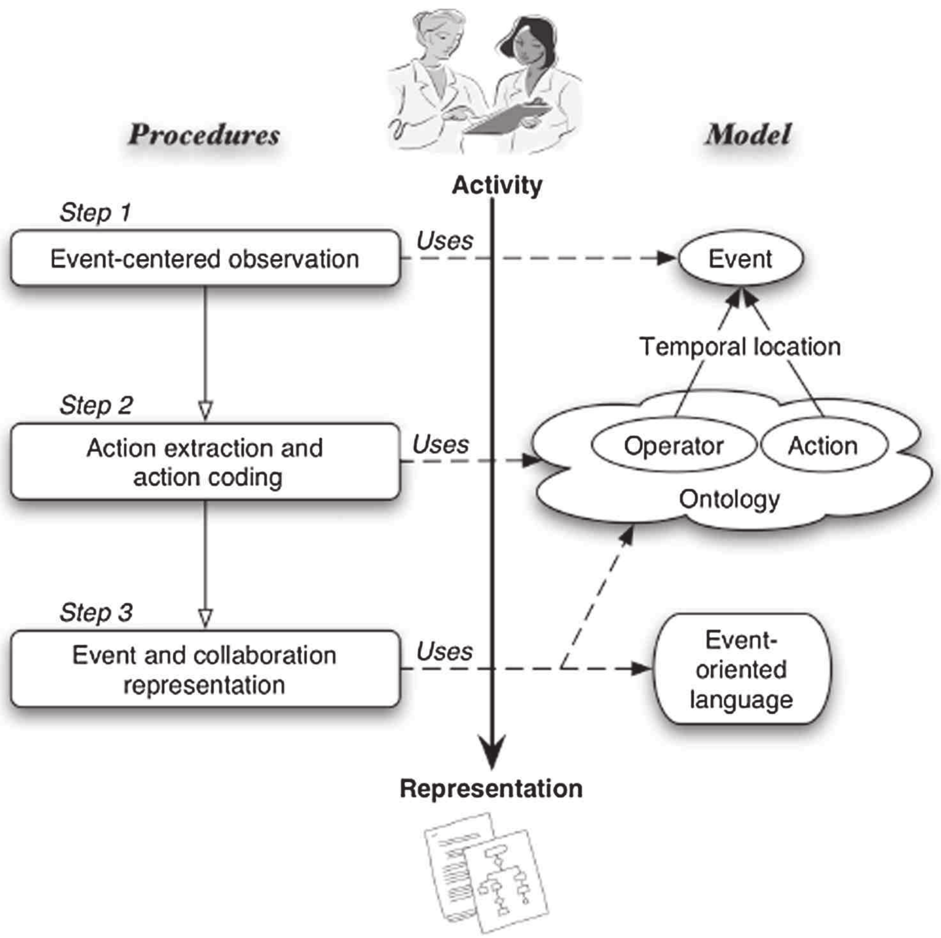

Fig. 1. The EORCA (Event Oriented Representation for Collaborative Activities) method (Pellegrin et al., 2005).

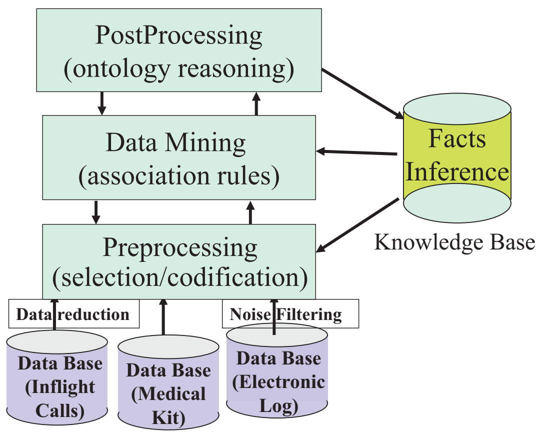

Fig. 2. Proposed method for knowledge discovery from databases.

Data reduction strategies (see Fig. 3) include dimensionality reduction, data compression and discretization (with particular importance especially to change quantitative data into qualitative data) and concept hierarchy generation. Concerning dimensionality reduction, feature selection is interesting to select a minimum set of attributes that is sufficient for the data-mining task.

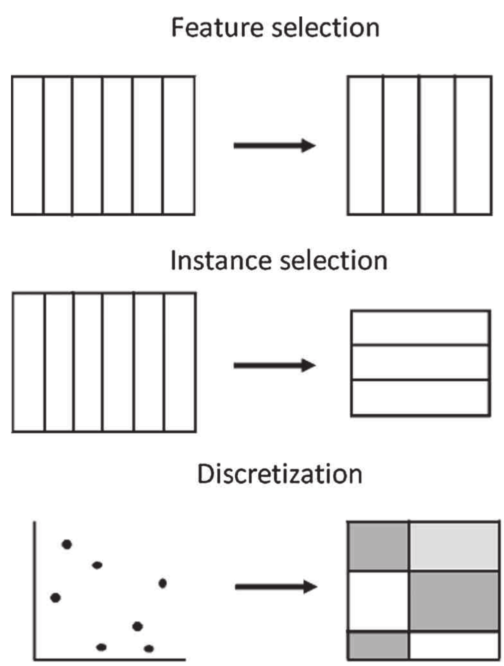

Fig. 3. Preprocessing with data reduction strategies (García et al., 2016).

Instead of a direct observation, we will treat secondary data from various sources using data mining tools. Verification of the consistency of the different sources would make it possible to exploit the most complete data (Peterson et al., 2013; Costa, 2015).

3.1.1. *Feature selection of In-flight Medical Incidents (IMI)*

The selection of relevant features is given by the preference of simple models against more complex ones. The key objective is therefore to obtain a subset of features describing correctly a given problem (García et al., 2016). In this manner, the feature selection provides the following benefits (Chandrashekar & Sahin, 2014):

- More accurate models: irrelevant and redundant features could yield accidental correlations in data mining algorithms, causing in models with low generalization capabilities.
- Reduction of the search space: the combination of selected or not selected features defines the search space that a data mining algorithm has to explore.
- Saving storage: irrelevant features are removed and accordingly their storage is not necessary.
- Reduction of costs: the reduction of features could be taken into account in the data collection task, besides implying a reduction of costs in sensing, actors and time consumption.
- Better understanding and visualization of data: the models learned from littler features will be simpler, making the results achieved easier to understand.
- Decrease of the over-fitting risk: in order to avoid that the learning algorithms over-fit the obtained models to the training data, the performances of algorithms are improved on unseen cases.

In the considered research context, the feature selection is used, for instance, during the process of knowledge discovery from data related to In-flight Medical Incidents (IMI).

In-flight medicine is an emergency medicine that has become a recognized specialty in France since 2015. The transversal nature of emergency medicine (general medicine, resuscitation, traumatology, psychiatry ...) and avionics environment make the management of medical incidents rather difficult.

There is no clear definition of the in-flight medical incident and this leads to poorly exploitable data. Each incident probably describes the product of a combination of factors, including patient's co-morbidity, the in-flight environment (Costa, 2015). Hence, it is a necessary to make a pre-processing of data before being able to pass them on Data mining tools.

Before the processing of data, there is a need to apply a data preprocessing on the considered three main data sources. We chose to work on the data reported by Costa (2015), Peterson et al. (2013), and Mahony et al. (2011). The interesting point here is the chronology of these works and the themes exposed that cover the main problems of handling medical incidents in the airplane (see Table 2).

Table 2
Number of incidents reported by the literature.

Authors of works	Number of incidents
Costa (2015)	69 incidents
Peterson et al. (2013)	11,920 incidents
Mahony et al. (2011)	11,329 incidents

For the same incident, the authors of works reported in the literature can use different names (as is often the case). To make possible the harmonious and consistent work with data from various sources, a preliminary semantic mapping work has been required. The result of the semantic mapping is shown in the following Table 3. Incidents with the same identifier are in the same semantic category. In the third column, we can see the ratio of each type of emergencies that include chronic medical conditions such as cardiac, pulmonary, neurological, or gastro intestinal disorders.

3.1.2. *Codification of In-flight Medical Incidents (IMI)*

This subsection is about the codification of In-flight Medical Incidents (IMI) in the preprocessing phase of knowledge discovery from databases.

Our codification transaction template is defined as follows:
T: IR, TI, RU, PCH, AD, HA
T: Transaction
IR: Incident Reported
TI: Type of Incident
RU: Resource Used
PCH: Patient Characterization (signs, symptoms, medical history)
AD: Aircraft Diversion
HA: Hospital Admission.

A number represents all instances of items. For the type of incident, this number corresponds to the ID column in Table 3.

The data reported in the literature do not allow building a transaction with more than three items. With the data in the previous of Peterson and its colleagues (Peterson et al., 2013), we can extract transactions with 3 items (IR, TI, AD), (IR, TI, HA).

We find a lack of data to define transactions with all our items. Yet these features are taken into account in studies, some of which show a strong correlation between the available resources (material and human elements) and the diversion of the aircraft (Peterson et al., 2013), or reporting of missing, poor quality, defective or unreliable equipment (Costa, 2015). However, the way in which data are reported is not suitable. In these studies, there is often an overall description of the transactions, and not a transaction-by-transaction description that would make it

Table 3
The semantic mapping of reported in-flight medical incidents.

Peterson et al. (2013)			Mahony et al. 2011			Costa (2015)		
Incident	ID	%	Incident	ID	%	Incident	ID	%
Syncope or pre-syncope	2	37.4	Unconscious: rapidly recovered	2	41.1	Syncope	2	46.4
Respiratory symptoms	3	12.1	Unconscious: slow or delayed recovery	2	1.5	Respiratory symptoms	3	8.7
Nausea or vomiting	4	9.5	Unconscious: no recovery	2	1.2	Nausea and vomiting	4	15.9
Cardiac symptoms	5	7.7	Breathing difficulty	3	15.9	Cardiac symptoms	5	2.9
Seizures	6	5.8	Nausea/vomiting/diarrhea	4	19.5	Epileptic seizure	6	2.9
Abdominal pain	7	4.1	Seizure	6	1.1	Pain (chest)	7	5.8
Infectious disease	8	2.8	Chest pain	7	2.3	Infectious diseases	8	4.3
Agitation or psychiatric symptoms	9	2.4	Behavioral	9	3.2	Agitation (4) or psychiatric symptoms	9	4.3
Allergic reaction	10	2.2	Allergic/skin	10	2.3	Allergic reaction	10	1.4
Possible stroke	11	2	Injuries	12	2.5	Injury, wound	15	2.9
Trauma, not otherwise specified	12	1.8	Collapse injury sustained	15	0.6	Obstetrical or gynecological symptoms	16	1.4
Diabetic complication	13	1.6	Limb swelling (panaris costa)	15	0.5	Thrombosis	20	2.9
Headache	14	1	Pregnant/in labor	16	0.1			
Arm or leg pain or injury	15	1	Pain-no other symptoms	17	5			
Obstetrical or gynecological symptoms	16	0.5	Congested/fever	20	1.1			
Ear pain	17	0.4	Bleeding no injury	20	0.7			
Cardiac arrest	18	0.3	Limb/facial weakness	20	0.2			
Laceration	19	0.3	Urinary	20	0.1			
Other	20	6,9	Advice/undetermined	21	1			
Unknown	21	0.1						

possible to better exploit this data. This problem is evoked by (Hinkelbein et al., 2017) in these terms: ûSeveral studies on the content of medical equipment have been published in recent years but these fail to address the utility of the equipment in the context of the medical emergencyý.

Therefore, now our transactions consist of a combination of two items T: IR, TI.

Without semantic mapping, Table 4 shows how Text Clustering Algorithm organizes incidents reported by Peterson (starting with 1) and incidents reported by Mahony (starting with 2). Incidents in the right column do not match, which is not semantically true. This semantic correspondence shows the importance of a semantic clarification of the various notions involved in the descriptions of in-flight medical incidents during the pre-processing phase (Fig. 3).

3.2. Data mining with association rule mining

In the data mining, we are interested by the discovery of interesting patterns in the database. Given a database, we want to discover patterns that can be novel, unexpected and useful. For example, it is a useful task to discover new relationships between in-flight medical incidents and diseases. This knowledge discovery can lead to the development of new preventive and corrective measures.

The task of frequent pattern mining was proposed by Agrawal and Srikant (1995):

- Input: a transaction database and a parameter minsup ≥ 1.
- Output: the frequent item sets (all sets of items appearing in at least minsup transactions).

Frequent pattern mining has many applications such as economics, health, and education(Fournier-Viger, Lin, Kiran, & Koh, 2017). However, it has important limitations (Alkan & Karagoz, 2016): (i) many frequent patterns are not interesting, (ii) quantities of items in transactions must be 0 or 1, and (iii) all items are considered as equally important (having the same weight). High-Utility Sequential Pattern Mining (HUSPM) is an extension of Weighted Sequential Pattern Mining where not only item weights are considered, but also item quantities in sequences (Lan, Hong, Tseng, & Wang, 2014). The goal of HUSP is to find all sequential patterns that have a utility greater than or equal to a minimum utility threshold in a sequence database.

3.2.1. SPMF algorithms

We use an Open-Source Data Mining Library (SPMF) specialized in pattern mining (Fournier-Viger, 2017) and it offers implementations of over a hundred data mining algorithms (Sequential Pattern Mining, Sequential Rule Mining, Sequence Prediction, Frequent Itemset Mining, Periodic Pattern Mining, High-Utility Pattern Mining, Association Rule Mining, Clustering, Time series mining, Classification and Text mining). Data mining algorithms in SPMF use a transaction database and there are algorithms that use sequence databases. In this research work, data mining algorithms are used to drill deeper into the in-flight medical emergency data. Each transaction is a set of items and item corresponds to the system's features.

For the purpose of this article, we consider the management of each incident as a transaction and as an "Item" any action or consideration that characterizes the care and the patient.

Table 4
Text clustering algorithm execution.

Incidents with correspondence		Incidents without correspondence	
13	Nausea or vomiting	11	Syncope or presyncope
21	Nausea/vomiting/diarrhea	12	Respiratory
118	Cardiac arrest	17	Infectious disease
14	Cardiac	18	Agitation or psychiatric
15	Seizures	110	Possible stroke
212	Seizure	111	Trauma, not otherwise specified
16	Abdominal pain	112	Diabetic complication
24	Pain – no other symptoms	113	Headache
27	Chest pain	116	Gynecology or obstetrics
117	Ear pain	119	Laceration
19	Allergic reaction	120	Other
28	Allergic/skin	121	Unknown
215	Bleeding no injury	23	Breathing difficulty
216	Collapse injury sustained	25	Behavioral
26	Injuries	211	Congested/fever
114	Arm or leg pain or injury	214	Advice/undetermined
21	Unconscious: rapidly recovered	219	Urinary
29	Unconscious: slow or delayed recovery	220	Pregnant/in labor
210	Unconscious: no recovery		
217	Limb swelling		
218	Limb/facial weakness		

To construct the SPMF input file, it was necessary to find the number of incidents in each study. By extrapolation, each percentage is multiplied by 10. Approximately 1000 transactions are obtained for each study. We have written a Python computer program to automatically generate SPMF input file.

We started by checking the correspondence of the names of the incidents used in the different studies. To do this, we applied a suitable algorithm for clustering texts using the Term Frequency–Inverse Document Frequency (TF–IDF) measure (Beel, Gipp, Langer, & Breitinger, 2016). This text clustering algorithm calculates number of clusters on its own and does transitivity clustering based on TF–IDF measure that is intended to reveal how important a word is to a document in a corpus of texts.

The lack of standardization of incidents management also prompted us to check the consistency of the information about these incidents. To do this, we use the association rule mining algorithms that are generally done in two phases: mining frequent itemsets in a transaction database, and then using these itemsets to generate the rules (Agrawal & Srikant, 1994). An association rule is a pattern of the form $X \rightarrow Y$ where X and Y are two itemsets such that $X \cap Y = \emptyset$. The mapping of the incident categories makes it possible to process the data of the 3 studies at the same time.

3.2.2. Association rule mining of in-flight medical incidents

The other aspect of the data we wanted to verify was consistency. For this purpose, the Apriori Association Rules algorithm was applied to the combined data set (Costa, 2015; Peterson et al., 2013; Mahony et al., 2011). The result can be seen in Fig. 4 and Table 5. The results show similar trends in different works. Besides this data validation, this work improves the categorization of incidents.

Since different types of association rules can be generated from the considered data, it may be interesting to present to the end user (domain expert) the existing relationships between the types of rules identified, modeled using a considered knowledge representation formalism. Therefore, the tools associated to this knowledge representation formalism can provide reasoning mechanisms to analyze the structure and semantics of the knowledge produced. For the same reason, it is also interesting to provide the end user with a tool that includes mechanisms to filter the set of rules extracted according to their different points of view and/or their expectations in a particular situation.

3.2.3. Post processing with ontology reasoning for in-flight medical incident management

The ontologies provide the categories of concepts and their relations in order to support the formal definition of semantic content to advanced domain-specific applications of semantic knowledge with a consensual meaning (Pfeiffer & Pfeiffer, 2007). The adopted knowledge representation is based on ontologies that are interesting in knowledge

SPMF - Pattern vizualization tool 2.05

Patterns:

Pattern	#SUP:	#CONF:
1 ==> 2	1 276	0,426
1 ==> 3	367	0,122
1 ==> 4	449	0,15
1 ==> 5	106	0,035
1 ==> 6	98	0,033
1 ==> 7	122	0,041
1 ==> 8	71	0,024
1 ==> 9	99	0,033
1 ==> 10	59	0,02
1 ==> 11	20	0,007
1 ==> 12	43	0,014
1 ==> 13	16	0,005
1 ==> 14	10	0,003
1 ==> 15	50	0,017
1 ==> 16	20	0,007
1 ==> 17	54	0,018
1 ==> 18	3	0,001
1 ==> 19	3	0,001
1 ==> 20	119	0,04
1 ==> 21	11	0,004

Fig. 4. SPMF pattern visualization, Apriori Association Rules (minsup = 0.O1). The Pattern column contains the items and defines relationships (Transaction T: IR, TI). The number 1 indicates the occurrence of an incident and the other numbers represent the type of incident. The names of these incidents are shown in Table 5. The support represents the number of incidents and the confidence the percentage of each incident.

engineering, since they do not reduce the choice of tools and methods of the following layers. The choice of ontologies at the conceptual level opens many possibilities at the logical (AI) level. Indeed, they are adapted to formalisms such as description logics and conceptual graphs as well as to typed, intuitionistic logic and fuzzy logics. Early anticipation and knowing the difficulty of finding in a single formalism all the characteristics necessary to build the required system, ontologies are a good option to be able to combine these formalisms and achieve certain objectives. This is the case, for example, with Datalog that is a declarative logic programming language, which is often used as a query language for deductive databases. Ontologies are useful for knowledge modeling and representation and they include elements (e.g. rules and axioms) associated to a reasoning capacity that is very important for knowledge-based systems. This reasoning capacity comprises the management of inference procedures (with possibly constraints checking) that are interesting in a collaborative approach to problem solving.

Flight crew members are trained in some care but in-flight commercial supply care is provided in almost all cases by a volunteer recognized as a health professional. If health

Table 5
Pre and post treatment incident categorization, this table combines Fig. 13 with the name of the incidents and the confidences indicated in the different studies. The confidence of the incidents varies, but the distribution of the types of incidents remains the same.

Pattern	#SUP:	#CONF:	Incident	Peterson	Mahony	Costa
1 ==> 2	1276.0	42.5901202	Syncope or presyncope	37.4	43.8	46.4
1 ==> 3	367.0	12.2496662	Respiratory symptoms	12.1	15.9	8.7
1 ==> 4	449.0	14.9866489	Nausea or vomiting	9.5	19.5	15.9
1 ==> 5	106.0	3.53805073	Cardiac symptoms	7.7		2.9
1 ==> 6	98.0	3.27102804	Seizures	5.8	1.1	2.9
1 ==> 7	122.0	4.07209613	Abdominal pain	4.1	2.3	5.8
1 ==> 8	71.0	2.36982644	Infectious disease	2.8		4.3
1 ==> 9	99.0	3.30440587	Agitation or psychiatric symptoms	2.4	3.2	4.3
1 ==> 10	59.0	1.96929239	Allergic reaction	2.2	2.3	1.4
1 ==> 11	20.0	0.66755674	Possible stroke	2		
1 ==> 12	43.0	1.435247	Trauma, not otherwise specified	1.8	2.5	
1 ==> 13	16.0	0.53404539	Diabetic complication	1.6		
1 ==> 14	10.0	0.33377837	Headache	1		
1 ==> 15	50.0	1.66889186	Arm or leg pain or injury	1	1.1	2.9
1 ==> 16	20.0	0.66755674	Obstetrical or gynecological symptoms	0.5	0.1	1.4
1 ==> 17	54.0	1.8024032	Ear pain	0.4	5	
1 ==> 18	3.0	0.10013351	Cardiac arrest	0.3		
1 ==> 19	3.0	0.10013351	Laceration	0.3		
1 ==> 20	119.0	3.97196262	Other	6.9	2.1	2.9
1 ==> 21	11.0	0.36715621	Unknown	0.1	1	

professionals do not answer (fear of legal problems), medical care can be provided by a crew member or a medical student (Bukowski & Richards, 2016). The ontologies facilitate the Clinical Pathway formalization in the context of a medical assistance in commercial flight. The involved volunteers (doctor on board staff) for medical care can collaborate with ground teams through telemedicine applications.

By Clinical Pathway formalization, we propose a medical assistance in commercial flight and a framework of telemedicine applications. This system will assist the volunteers (doctor on board staff) for medical care and will serve as a telemedicine framework with ground teams. Telemedicine is a remote medical practice using information technologies and telecommunication (Sene, Kamsu-Foguem, & Rumeau, 2015). This is an opportunity for safety of life applications like aviation and maritime transport where medical evacuation can cost too much.

Building a knowledge-based system can be divided into two main stages: (i) modeling and representation of knowledge; (ii) implementation of the interaction mechanism between the different agents using algorithms. This step defines how knowledge is used to solve problems.

Clinical Pathway that is used as a knowledge base provides an effective description of medical management from Practice Guidelines. It is a tool that not only formalizes the prediction of acts but also defines their meaning: infectious risk, risk of anxiety (Psiuk & Gouby, 2013), which is indispensable in our context. Indeed, the formalization of the prediction of acts is necessary in the case of emergencies such as an in-flight medical incident and especially in the absence of a physician. This appropriateness of the Clinical Pathway with our context emerges through its difference with the guidelines and other algorithms: "Clinical Pathways differ from practice guidelines, protocols and algorithms as they are typically: (1) utilized by interdisciplinary Team; (2) focus and the quality and coordination of care" (Bellomo, 2011). Clinical Pathways are usually focused on the quality and effectiveness of care after decisions on procedures and services are made using best practice rules. Clinical Pathway details the care process containing concrete clinical interventions for intended outcomes and fit into multidisciplinary (Ye, Jiang, Diao, Yang, & Du, 2009), which makes it interesting for the application of telemedicine.

Another aspect which reinforces the choice of the Clinical Pathway whose structure is visible in Table 6 is the granularity of the decision (CDSS output). The study of the existing CDSS shows an insufficiency of their output to manage in-flight medical incidents. Diagnostic CDSS have as output the type of disease. Many therapeutic CDSS offer a type of care as output (Doumbouya, Kamsu-Foguem, Kenfack, & Foguem, 2015). There are some CDSS that propose care procedures (admission, surgery, discharge) (Huang, Lu, & Duan, 2012), but are not suitable for in-flight medical incident management.

We chose the medical action as the output of our CDSS. Our system must indicate the good medical action at the right time.

A knowledge-based system provides the user with a knowledge base and an automatic means to reason about this knowledge (Bentahar, Moulin, & Bélanger, 2010). We construct our CDSS in three stages corresponding to the representation levels necessary to transform the knowledge from an abstract definition of a machine representation. These levels define syntactic and semantic rules to describe problems (Pfeiffer & Pfeiffer, 2007). This is more complete than the Shapiro layer model and less complicated than the Newell model, we will use Brachman model (Brachman, 1978).

Table 6
Clinical Pathway consists of targets (observations). Each target defines a set of actions and for each action its beginning, duration, periodicity.

Clinical Pathway		
Target 1	Action 1	Start, duration, period
	Action 2	Start, duration, period
	Action 3	Start, duration, period
Target 2	Action 2	Start, duration, period
	Action 4	Start, duration, period

In order to have a low layer comprehensible by the machines and the humans and thus facilitate the conceptualization, the layers of the Brachman model were reduced by eliminating the linguistic layer. Also, due to the proposed codification choices (logical level), the epistemic and logical layers have been merged. Besides, in the end we have renamed the conceptual level of the model we have chosen in this case, the ontological model.

Fig. 5 shows the functional architecture of our decision-support system. We wanted a system that benefits both from the advantages of the open world system of ontologies, but also from the capability of computer language processing. For this, we decided to interface the ontology management tool (here Protégé developed by the Stanford Center for Biomedical Informatics Research at the Stanford University School of Medicine (Musen, 2005)) with a programming language.

In the work on the CDSS, (Zhang, Tian, Zhou, Araki, & Li, 2016) proposes architecture similar to what we want to build, but their work is not done in the context of telemedicine or in the avionics context.

We use OWL2 API ("OWL API," n.d.), which makes it easy to develop computer programs. The basis of the rules and the one containing the queries of the knowledge base are not in the same place because they are not exploited by the same people.

By defining the layer model, one defines the method of construction of our system whose steps are:

- Modeling the concepts and processes characterizing our system.
- The representation of all this information under a given formalism.
- Automation of decision-making processes

4. Result and discussion

To model a medical care process, it is necessary to: (1) Find all the concepts necessary for the characterization of the situation, (2) define the processes linking these concepts. For the step (1), we use medical nomenclatures and for the step (2) as indicated in the introduction, the clinical pathway is used.

4.1. Conceptual level

Fig. 6 shows the main concepts used to characterize the medical incident situation in a commercial aircraft. A patient (passenger) has symptoms that may correspond to a Clinical Pathway. Each Clinical Pathway defines a set of target incidents corresponding to the problems that need

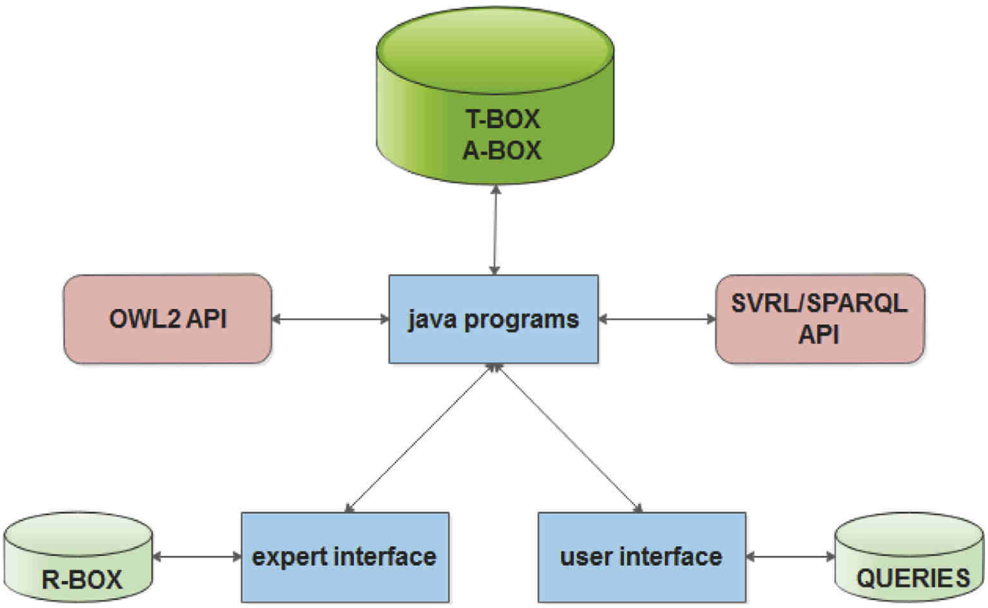

Fig. 5. Functional architecture.

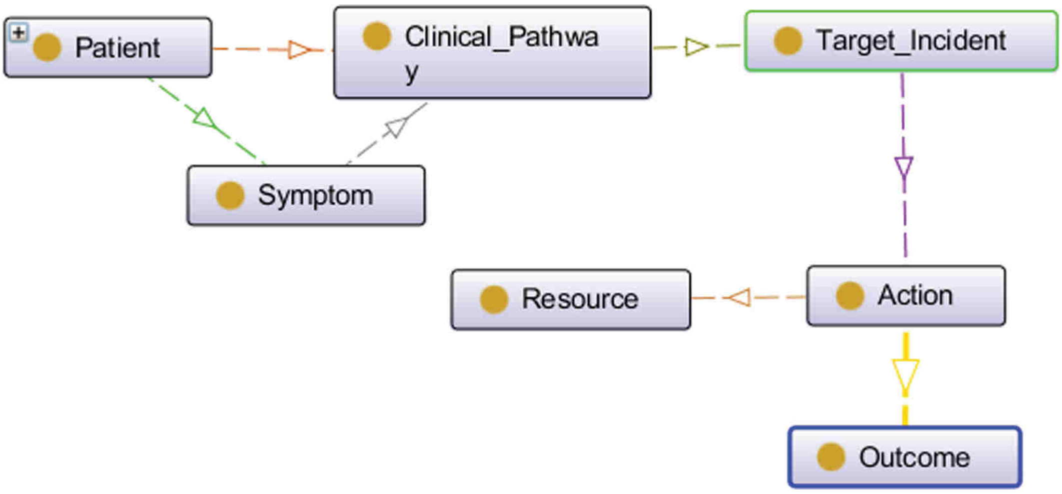

Fig. 6. Characterization of in-flight medical environment.

to be addressed. These problems are solved through actions that require resources. Actions produce results through the delivered outcomes.

Patient: passenger with medical incident.

Symptom: Symptoms observed on the patient.

Clinical Path: Care Process.

Target Incident: We will focus on the definition of this concept. Target incidents are the main components of Clinical Pathway and represent the issues to be addressed when a medical emergency occurs. We use the type of Clinical Pathway proposed in the previous work described in Psiuk and Gouby (2013), which is constructed using a Care Plan and which defines the targets to be treated from the clinical areas. This choice is to be explained by the richness and clarity of their approach, in particular the separation of clinical domains into three categories instead of two, distinguishing human reactions, complications related to the pathology and side effects of treatment.

For any person suffering from a medical incident or with a specific pathology, three clinical are defined:

- Signs and Symptoms,
- complications related to the pathology and side effects of treatment,
- physical and physiological human reactions.

The last two domains are defined from the first.

Clinical Pathway organizes the interventions defined for the management of observations in each clinical field. Some observations for a child with acute gastroenteritis are shown in Table 7 (Psiuk & Gouby, 2013).

Action: medical interventions to treat target incidents.

Resource: material, human resources available to manage medical problems.

Outcome: the result of actions.

At the conceptual level, the Clinical Pathway contains target incidents that are treated using actions. These actions may be dependent and their scheduling corresponds to the in-flight medical incident management.

An approach based on clinical pathway ontologies has been proposed to facilitate computerization (Ye et al., 2009).

Analyzing Clinical Pathway is useful in order to determine the essential medical behaviors, (Huang et al., 2012) and we consider the Clinical Pathway as a succession of clinical events. A clinical event is a clinical activity performed in a time t (event e = (activity a, time t)).

We combine these two approaches for the formal and temporal aspects. Thus we add the concepts Inputs, Outputs, Preconditions to manage the dependence between actions (Fig. 7) (Doumbouya, Kamsu-Foguem, Kenfack, & Foguem, 2018; Saadati & Denker, 2010).

Our clinical pathway is a succession of events that can be described as actions, each action having a constraint of execution. The challenge in the automation phase will be to find the best scheduling algorithms.

Table 7
Target incidents in the case of acute gastroenteritis.

Signs and symptoms	Complications related to the pathology and side effects of treatment	Physical and physiological human reactions
o Diarrhea	o Risk of contamination of parents, siblings	o Parental anxiety
o Vomiting	o Risk of shock (hypovolemic, toxic infective)	o Children’s crying
o Weight loss	o Shock (hypovolemic, toxic infectious)	o Risk of agitation of the child
o Abdominal pain	o Risk of extravasation	o Agitation of the child
o Fever	o Extravasation	o Ability of parents to manage return home
o Dehydration	o Neurological disorders on ionic disorders	
	o Irritation of the seat	
	o Risk of pain	

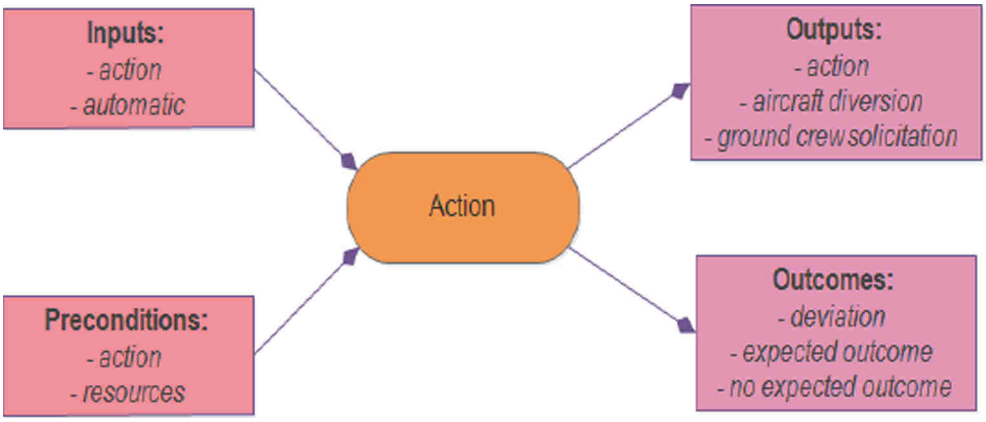

Fig. 7. Structured analysis of the links between actions.

$$CC = [(\text{action a1}, \text{constraint ce1}),\\ (\text{action a2}, \text{constraint ce2}) \ldots]$$

4.2. Logical level

The representation layer takes as input the model defined at the previous level. This level must ensure both syntactic and semantic interoperability.

We will use the description logic and OWL as the representation language. This offers certain interoperability because OWL constitutes a tool very used in the construction of medical ontologies (SNOMED CT (Lee, Cornet, Lau, & de Keizer, 2013); UMLS (Patel & Cimino, 2009) . . .).

As a platform for the construction and manipulation of ontologies, we will use "Protégé" which is a reference but also another platform for development, Eclipse (Silva, 2009). By interacting programming languages and ontolo-

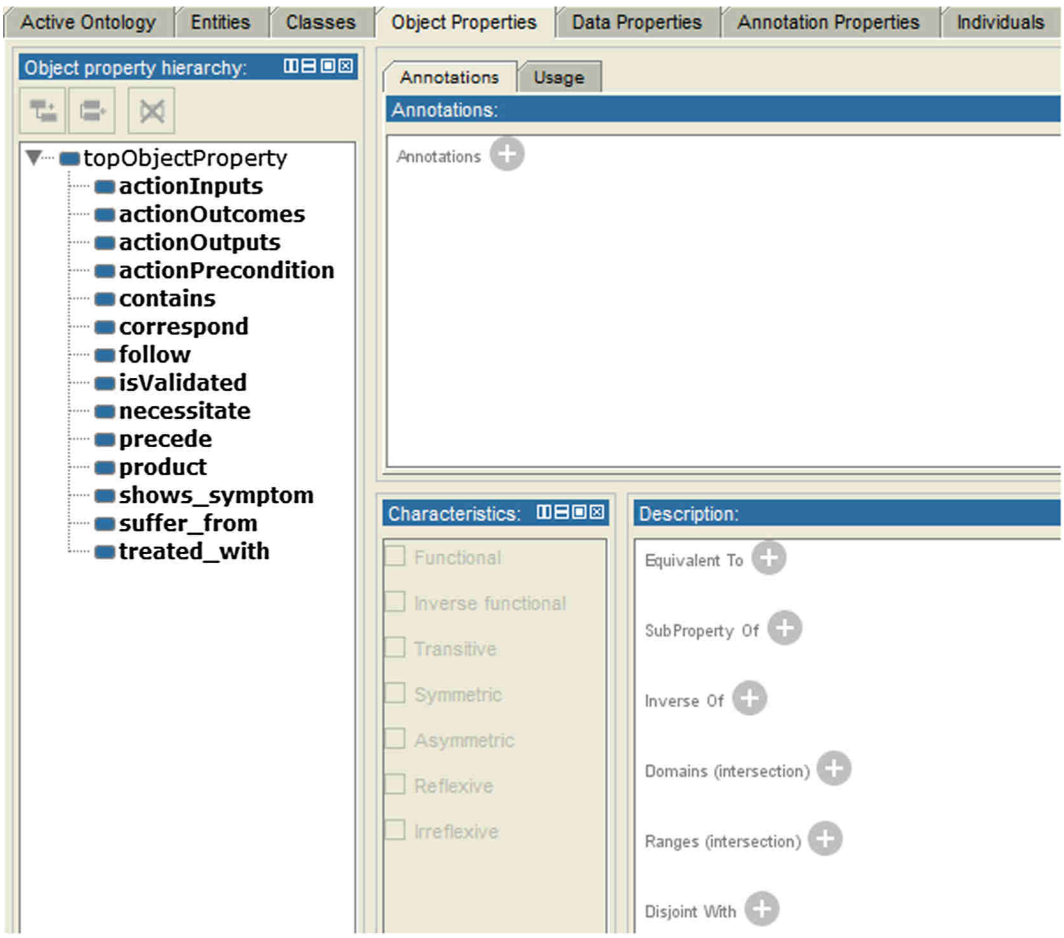

Fig. 8. Characterization of concepts.

gies, we increase flexibility of content management with a greater computing capacity. This is especially important for the implementation layer. In the next two figures (Figs. 8 and 9), we have constructors for the characterization of concepts and roles.

4.3. Implementation level

This level implements the technical architecture of our system. Part of this architecture (the TBOX) is already built in the conceptualization phase.

The java program relies on the OWL2 API library as described earlier. As the objective of the proposed work is to develop documentation CDSS, our java program is composed of three types of functions:

– Ontology component creation functions (classes, individuals, and rules) (Fig. 10).
– Ontology creation
– A main function in which the data output format is defined.

These functions make it possible to exploit knowledge such as SNOMED CT and by relying on the processing of data from the literature; they provide relevant documentation for the medical assistance of passengers.

4.3.1. A-BOX (Assertional-Box)

An ABox (Assertional Box) is a fact associated with a terminological vocabulary within a knowledge base. It describes relations between instances and concepts. In this study, ABox statements are associated with instances of concepts corresponding to the context of in-flight medical emergencies.

For this, we have several options:

– Exploitation of medical ontologies (SNOMED CT, ICD)
– Use of Clinical Pathway defined by experts

As we will see, the interfacing of the ontologies with the programming languages will facilitate the definition of the A-BOX.

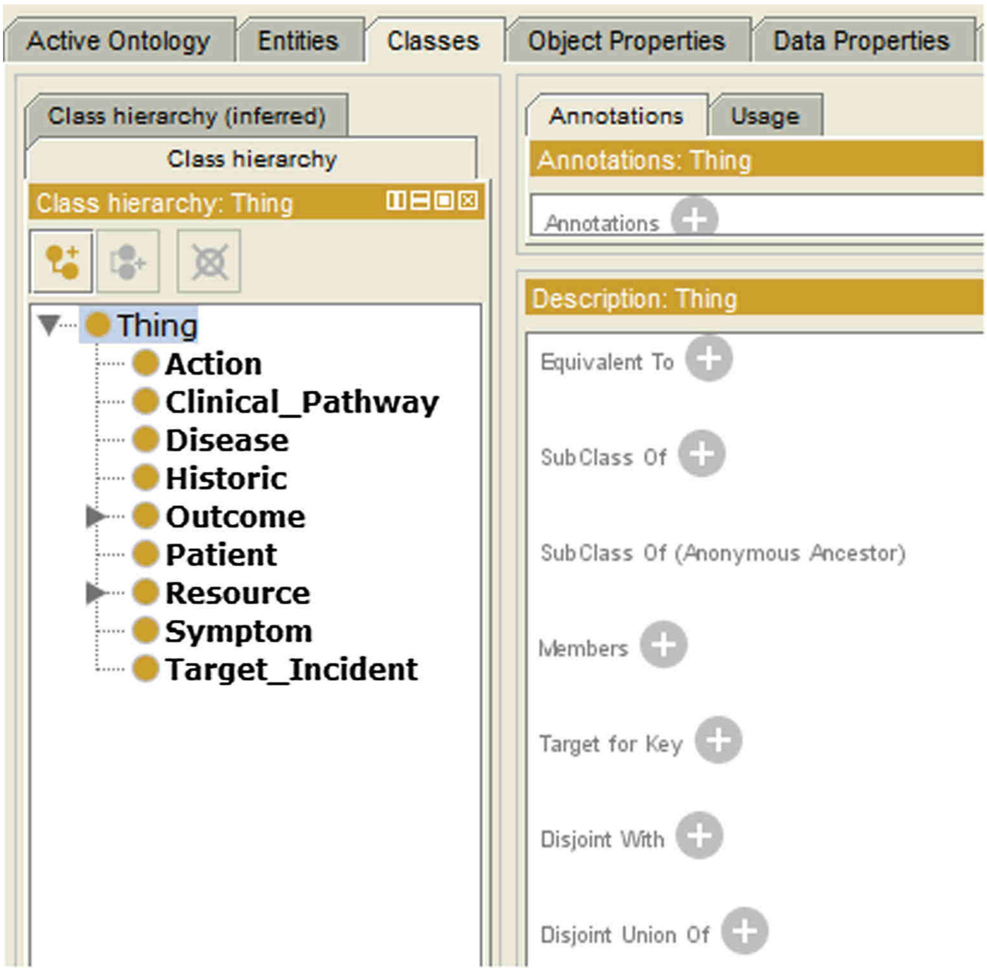

Fig. 9. Characterization of relationships.

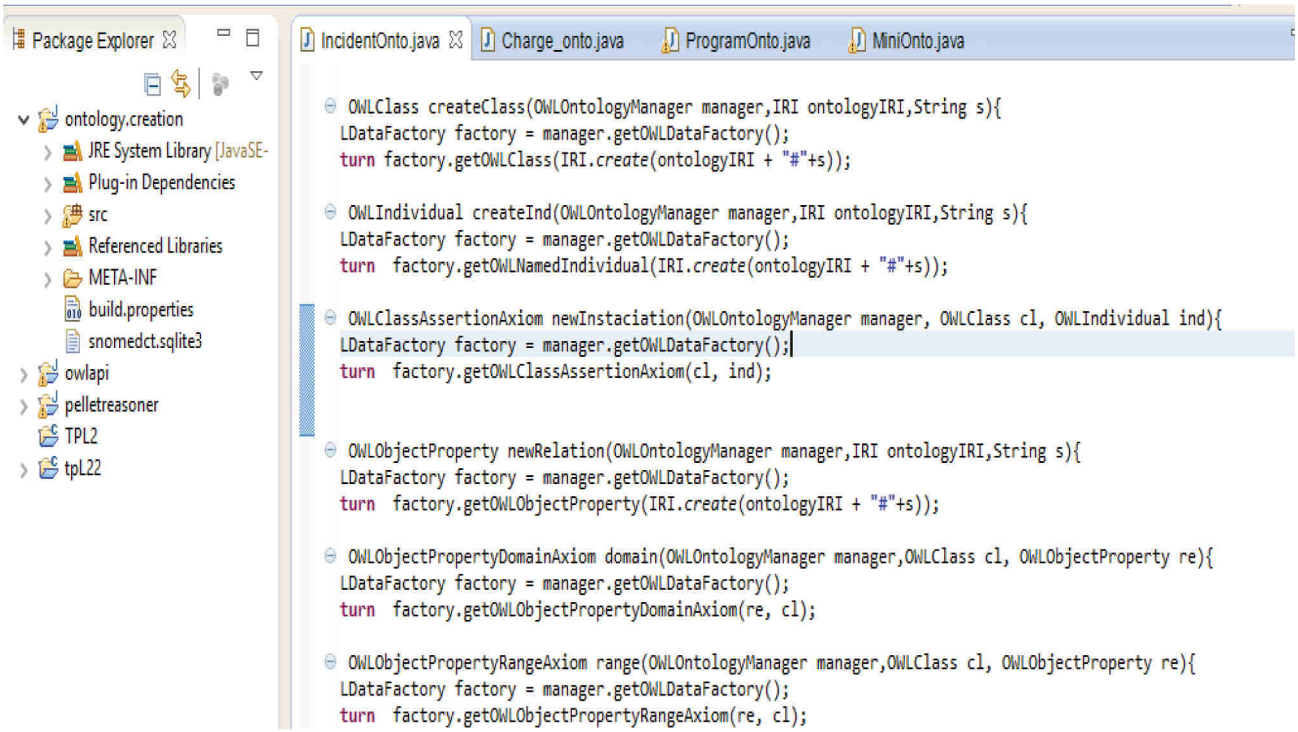

Fig. 10. Ontology component with functions attached to program units.

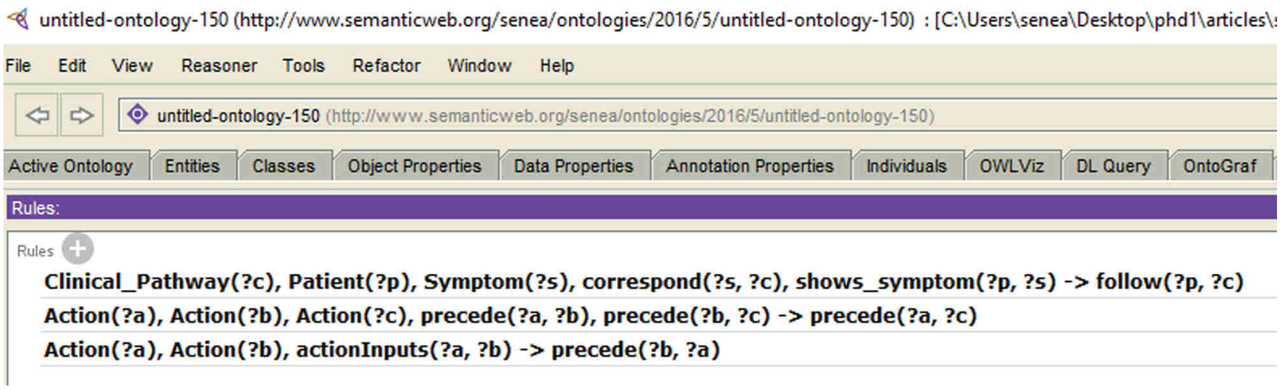

Fig. 11. The rules facilitate the creation of the knowledge base. For example, if we assume that A1, A2 and A3 are actions, to support an incident management, if A1 "precede" A2 and A2 "precede" A3 then a relation A1 "precede" A3 is automatically added. If A1 "actionInputs" A2 then a relation A2"precede" A1 is automatically added.

4.3.2. R-BOX (Rules-Box)

Although they do not play a major role at the moment (CDSS documentation), here are some rules defined in "Protege" (relationship between Patient and Clinical Pathway, transitivity of the temporal relationship called precede, temporal descriptions of events with a relation between action and Inputs) (Fig. 11).

4.3.3. Discussion

4.3.3.1. High-utility sequential patterns mining (HUSPM).

HUPs (High-utility Patterns) are defined by assigning weights to items. This weight is set according to the importance given to an item. For example, the types of incidents with a large support and a confidence greater than 10% can be fixed as HUPs. In the context of In-flight medical incidents, HUPs can be viewed as problems related to Syncope, Respiratory symptoms and Nausea or vomiting. HUPs may also be considered to be the most fatal and diversionary incidents. Missing resources (i.e. missing or unsuitable equipment in the emergency medical kit) can also be seen as HUPs (Costa, 2015).

Finally, interesting conclusions can be drawn not only from the rules that are present after the extraction process, but also from the fact that some expected rules are missing. It therefore proves to be useful to show that comparing the present and the absent rules can help identify anomalies in the way in which an experiment is structured in the database, or can be used to determine more precisely the characteristics of processes studied in the target systems.

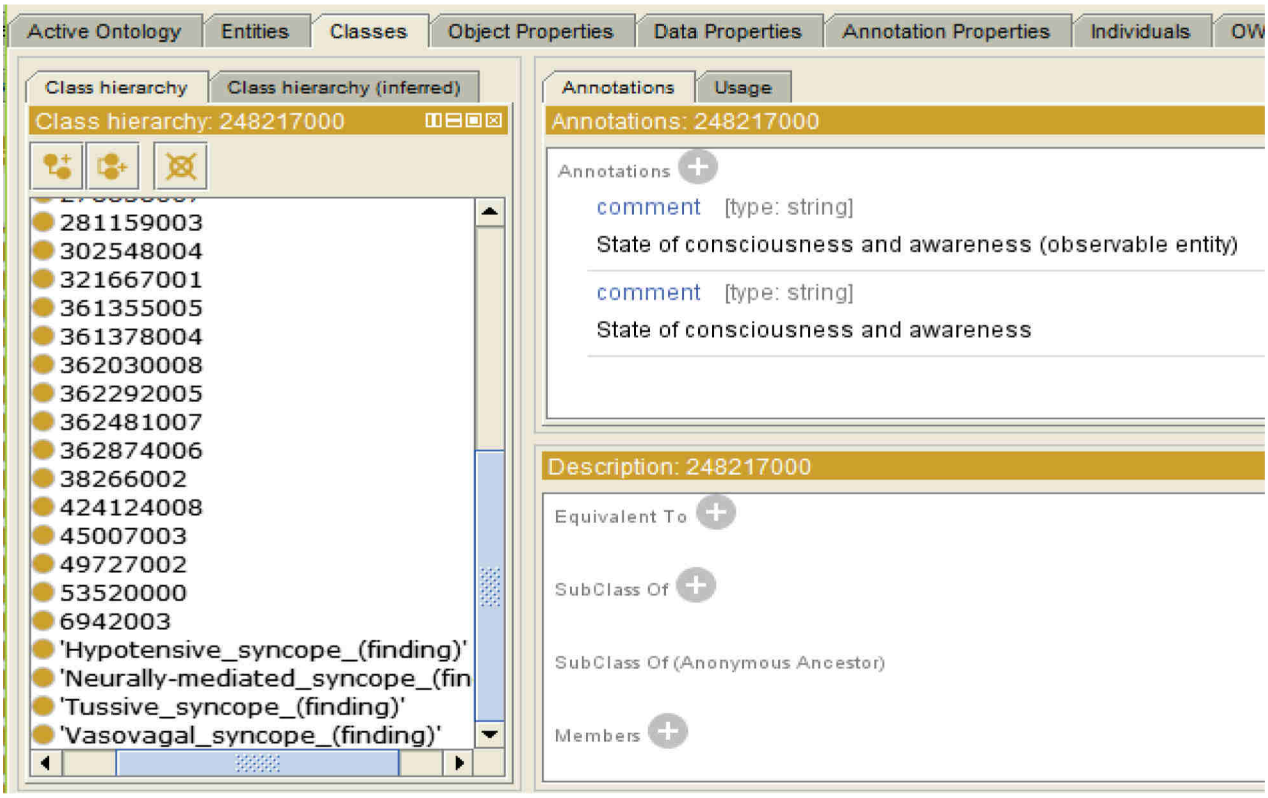

Fig. 12. Concepts for the syncope incident.

4.3.3.2. Ontology reasoning for In-flight medical incidents. The knowledge structures defined in the conceptual level and the implementation of the functional architecture of in-flight medical incident management enabled us to exploit the knowledge of SNOMED CT. Thus, the volunteer is provided with relevant data. For each medical term, one can exploit knowledge bases like SNOMED CT and thus build an ontology gathering the elements relating to this term (concepts, relation, individuals). For 'syncope' incident, the result can be seen in Fig. 12 (concepts) and Fig. 13 (relationships).

5. Conclusion

Knowledge extraction from databases is a fascinating research field in a globally connected and competitive environment. In that respect, data analysis techniques are generally expected to lead to more improved quality of services. This is especially the case for the aeronautic sector, which is subject to additional constraints related to the capacity to provide safety for passengers with an increasing numbers of people travel by air transport in various countries. These people may have different physical and/or psychological needs, behaviors, and vulnerabilities. Hence, the management of in-flight medical incident is a challenging topic for Commercial airline companies.

In this paper, a method is proposed for knowledge discovery from in-flight medical incidents databases. This method includes a preprocessing with feature selection and codification, data mining with association rule mining and the post processing with semantic clarification through ontology, which can make possible interpretation of obtained rules. The preprocessing is necessary to overcome the lack of standardization and structuring of information relating to the in-flight medical incidents with an assistance for the suitable documentation of these air travel events. The provision of coherent and consistent data is important to determine more accurate inflight incident numbers and facilitate their processing. The data mining using association rule mining is useful to output all association rules having a support (i.e. count of frequencies) and a confidence (i.e. assessment of the conditional probability) respectively no less than some thresholds set by the user. In the context of air travel, these association rules provide practical knowledge that can contribute to organize and carry out response actions to problems arising from in-flight medical incidents.

The post processing phase using ontologies explore medical provider's knowledge regarding the traceability of in-flight medical care. It also provides a semantic clarification that contributes to improve the understanding of passenger's knowledge about the medical clearance process. A formal knowledge representation of medical incident management procedures (categorization, investigative plan, etc.) constitutes a valuable and practical tool for continuous improvement of the safety level of the passengers during air travel.

Although this work has focused on the data associated to problems arising from in-flight medical incidents, it is possible to sketch out a list of possible actions and deter-

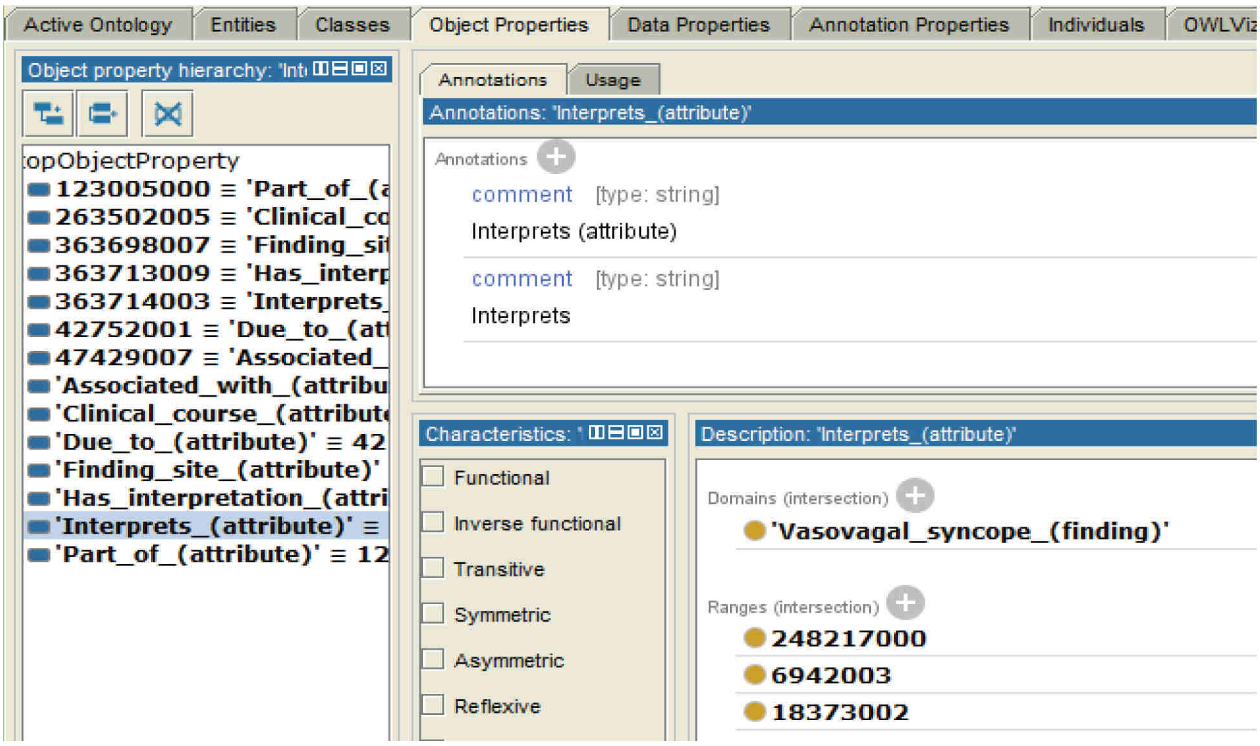

Fig. 13. Relationship for syncope incident.

mine the most appropriate strategies for decision-making support. The next step is to integrate a decision model under uncertainty into the system (Berger, Bleichrodt, & Eeckhoudt, 2013). This model will define what should be the evidential knowledge structures supporting the actions of a physician during an in-flight medical incident. Another important aspect not raised in this work is the user interface, which will play an important role in the usability and thus the acceptability of the system.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.cogsys.2018.01.002.

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