Data mining for decision support with uncertainty on the airplane

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A B S T R A C T

This study describes the formalization of the medical decision-making process under uncertainty underpinned by conditional preferences, the theory of evidence and the exploitation of high-utility patterns in data mining. To assist a decision maker, the medical process (clinical pathway) was implemented using a Conditional Preferences Base (CPB). Then for knowledge engineering, a Dempster-Shafer ontology integrating uncertainty underpinned by evidence theory was built. Beliefs from different sources are established with the use of data mining. The result is recorded in an In-flight Electronic Health Records (IEHR). The IEHR contains evidential items corresponding to the variables determining the management of medical incidents. Finally, to manage tolerance to uncertainty, a belief fusion algorithm was developed. There is an inherent risk in the practice of medicine that can affect the conditions of medical activities (diagnostic or therapeutic purposes). The management of uncertainty is also an integral part of decision-making processes in the medical field. Different models of medical decisions under uncertainty have been proposed. Much of the current literature on these models pays particular attention to health economics inspired by how to manage uncertainty in economic decisions. However, these models fail to consider the purely medical aspect of the decision that always remains poorly characterized. Besides, the models achieving interesting decision outcomes are those considering the patient's health variable and other variables such as the costs associated with the care services. These models are aimed at defining health policy (health economics) without a deep consideration for the uncertainty surrounding the medical practices and associated technologies. Our approach is to integrate the management of uncertainty into clinical reasoning models such as Clinical Pathway and to exploit the relationships between the determinants of incident management using data mining tools. To this end, how healthcare professionals see and conceive uncertainty has been investigated. This allowed for the identification of the characteristics determining people under uncertainty and to understand the different forms and representations of uncertainty. Furthermore, what an in-flight medical incident is and how its management is a decision under uncertainty issues was defined. This is the first phase of common data mining that will provide an evidential transaction basis. Subsequently an evidential and ontological reasoning to manage this uncertainty has been established in order to support decision making processes on the airplane.

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1. Introduction

The developments of Clinical Decision Support System (CDSS) have heightened the need to provide a deep and unified understanding of factors impeding or facilitating implementations of CDSS used by physicians [1]. Medical decision systems under uncertainty can help health-care providers to deal with the uncertainty inherent in many medical decisions. Probabilistic methods are the most used for the expression of this uncertainty. In particular, the adaptation of Expected Utility theory (i.e. preferences with regard to choices having uncertain outcomes) has been much discussed in the economics literature (e.g. Mathematical Economics [2] and Health Economics [3]).

These models, targeted at economics domain, are not always adaptable to the problems of medical decisions where the variables are hardly quantitative [4–7]. The associated methods generally use four types of decisions: “sick” and “not sick” if the medical problems are diagnosed, “treatment” and “no treatment” when making therapeutic decisions. Their decision support systems processes are incomplete. Thus, these methods quantify health status in terms of years of life expectancy.

A great deal of previous research into uncertainty has focused on other approaches like fuzzy logic [8]. The adequacy of one method or another often depends on the context. This study sets out to investigate the usefulness of belief functions approaches to the representation of medical uncertainty. This approach makes it possible to grasp the epistemic aspect of the information, thus preventing it from reducing its imperfection to its randomness. It also allows taking into account inconsistency and vagueness.

The factors determining tolerance of uncertainty can be divided into five groups [9], (1) care context, (2) physician-related factors, (3) patient-related factors, (4) relationship between the physician and the patient, (5) clinical reasoning and risk estimation.

For purposes of this study, three of these factors that provide in-flight medical decision support will be considered:

- Care context: commercial airplanes are still places where medical coverage is not optimal. Most health professionals intervening in this environment are doing it for the first time [10].
- Patient-related factors: mining data on in-flight medical incidents provides a knowledge base of past cases.
- Clinical reasoning and risk estimation: formalization of the clinical pathway provides assistance on care procedures and the use of incident data allows the risk estimation at each decision.

The main weakness with medical decision under uncertainty studies is the conceptualization of uncertainty. There is always a tendency to equate uncertainty with a risk situation, whereas according to Knight [11] “uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated.” The perception of medical uncertainty is not only behavioural, it is cognitive and emotional [12]. Studies point out the problem of complete quantification and computation [9]. Instead of trying to quantify the level of uncertainty about the decision maker, the threshold uncertainty determining factors will be considered (Fig. 1).

To assist in decision-making, it is required to provide provide tools for managing tolerance to uncertainty and this is what will be conducted using knowledge representation techniques and in-flight medical incident data mining. All these tasks will be organized into a Clinical Decision Support System (CDSS).

The architecture in Fig. 2 shows the interactions that can exist between a CDSS and a user. In addition to the user interface and the CDSS, record services and terminology services are two other important components. The first one is used to record patient's information and the second one contains medical terminologies that allow both syntactic and semantic interoperability, and plays a meta-model role. SNOMED Clinical Terms or SNOMED CT is used for terminology services, since it is the most comprehensive and defined clinical health terminology system in the world [13]. Its benefits include relevant information management, meaning-based retrieval, accurate retrospective reporting for research and additional opportunities for real time decision support.

This study aims to contribute to the growing medical decision-making area of research by exploring knowledge engineering, evidence theory and data mining for the purpose of an analysis of in-flight medical incidents. This contribution will be at different levels. Firstly, the factors determining the management of in-flight medical incidents will be transformed into items and matching them to the factors determining uncertainty. Secondly, the notion of high utility items to act on the decision maker's uncertainty threshold will be exploited. Our itemset utility is different from the utility of classical High Utility Itemset Mining (HUIM) [14–16]. In

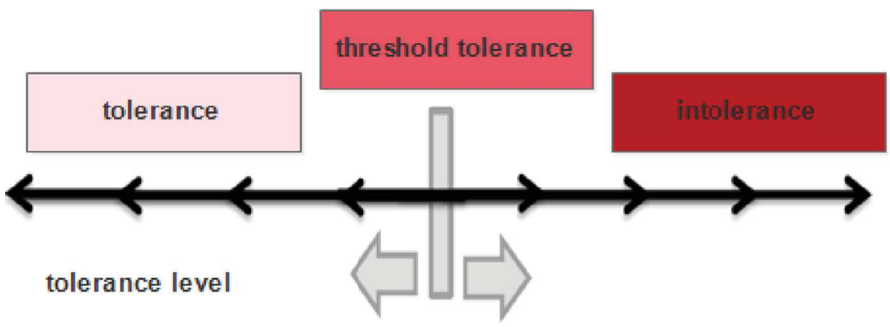

Fig. 1. The threshold of tolerance to uncertainty.

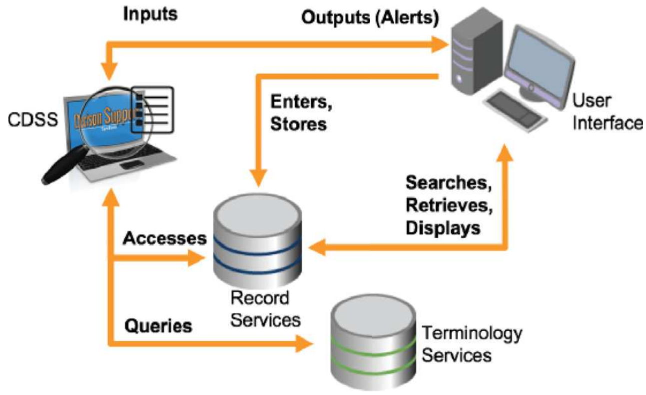

Fig. 2. CDSS interaction with EHR components.

general, information on itemset utility is in the form of quantities and costs. For us, it is the uncertainty of the decision-maker who defines high-utility itemsets. Also, this utility of our itemsets is comparable to the utility of probability models. Finally, the Clinical Pathway as a conditional preference base and defined algorithms to update the transaction database and determine High-Utility Itemsets (HUIs) will be formalized.

Our decision model integrates the aforementioned three characteristics. Therefore, a decision support system under uncertainty adapted to the clinical reasoning is proposed in this study. This system can accompany the "decision maker" in each choice of medical acts, specifically in the air transport sector.

It is expected that the temporal aspect between medical actions by the preferences modeling and the clinical pathway formalization is efficiently managed. To this end, attention or caution to the planning and decision-making processes is exercised. The uncertainty formalized with the theory of evidence will be integrated into ontologies by extending the similar previous works [17,18].

What is interesting with ontologies are their contributions to knowledge engineering but also the fact that they do not reduce the choice of tools and methods for the knowledge representation and reasoning. The choice of ontologies at the conceptual level opens many possibilities at the logical level. Indeed, they are adapted to formalisms such as description logics [19] and conceptual graphs [20] as well as to intuitionistic logic [21] and fuzzy logic [8]. 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 [22] that is a declarative logic programming language, which is often used as a query language for deductive databases. Decision-making will be based on ontological and evidential reasoning.

This paper is organized as follows. In Sections 2 and 3 the state of the art of in-flight-medical incidents and medical uncertainty representation approaches will be conducted. The description of evidential in-flight medical decision framework is examined in section 4. The discussion of our proposed methodology is examined in the fifth section before concluding in section 6.

2. In-flight medical incident feature engineering

Several systematic reviews of in-flight medical incidents have been undertaken [23] [24,25]. However, much of these studies up to now have been descriptive in nature. They (1) organize incidents differently; (2) give different names to incidents that are semantically identical, (3) use different languages, (4) and address to different issues. These studies are statistical, looking for relationships between incident management key variables (type of incidents, occupation of decision makers and diversions).

A large and growing body of literature has investigated in-flight medical incidents. Despite this there is no clear definition of an in-flight medical incident, and this leads to poorly exploitable data [10].

To this end, peer-reviewed secondary data, both quantitative and qualitative in-flight medical emergency studies was collected and analysed. This was achieved, firstly by conducting a systematic search on PubMed (i.e. database of references and abstracts on life sciences and biomedical topics) in June 2017 using key terms "in-flight medical incident" and "in-flight medical emergencies". Chandra and Conry identified relevant studies published between 1980 and 2010 [26]. Sand and its colleagues showed that a high number of incidents is among the most recent and most expressive [27].

Secondly, original research on websites providing access to a large database of scientific and medical research (e.g. PubMed and ScienceDirect) was conducted. High-quality studies published between 2010 and 2017 [25,28] and [10] were extracted. It emerged that some studies deal with specific aspects such as the problem of medical resources [29,30] and medical care [24].

Table 1 illustrates the wide range of estimates generated by analyzing in-flight medical data. The data considered retrospectively are collected over 10,000 cases in fairly long periods (5 years and 9 years) and airlines in different continents [27,28]. Peterson and colleagues provide data collected directly from the patient/passenger that has experienced an in-flight medical incident [25]. Costa sends a questionnaire to collect or investigate in-flight medical incidents from the general physicians on the French Indian Ocean island of Réunion [10]. Among the 97 responses gathered 69 physicians had an experience in health intervention with in-flight

Table 1
Study characteristics.

Authors	Journal	Dates	Study Design	Total of Cases reported
[27]	Critical Care	01/2002-12/2007	Retrospective 2 Airlines-Europe	10,189/5 years
[28]	Aviation, Space and Environmental Medicine	01/1996-12/2004	Retrospective Oceania based airline	11,326/9 years
[25]	New England Journal of Medicine	01/2008-10/2010.	domestic and international airlines to a physician-directed medical communications center	11,920/2 years
[10]	PhD thesis	02/2015-04/2015	Retrospective response of 97 general physicians in Reunion Island	69/3 months

medical incidents.

The pre-treatment necessary to create the evidential transaction base will be described in the section 4.1.2. Figs. 3 and 4 capture the background of in-flight medical incidents and the context in which incident management systems operate.

Fig. 3 shows stakeholders of in-flight medical assistance. The different stakeholders include physicians (48,1%), nurses (20,1%), flight crew members, other health professionals [25]. The diversion rate and relevance are correlated with the type of caregivers (Fig. 4).

Table 2 presents a set of variables and their type of factors determining tolerance of uncertainty.

3. The medical decision under uncertainty

3.1. Uncertain medical decision

The literature on medical uncertainty formalization has highlighted several approaches.

- **The probabilistic approach**

The most well-known approaches for assessing uncertainty are probabilistic.

According to a definition provided by Ref. [31]; a decision-making problem under uncertainty is a 4-tuple $\{S, X, A, \geq\}$ where S is a set of states of nature, X a set of consequences, $A = X^S$ a set of possible actions and $\geq$, a preference relation on A, generally complete and transitive. In decision-making under uncertainty acts are functions, f: $S \to X$.

In the Expected Utility model [32,33], the preference relation is a probability utility function defined in X (u: $X \to [0,1]$). Uncertainty is represented by probabilities and the decision criterion is simply the maximization of the expectation of satisfaction provided by decisions.

$$E_{pu}(h) = \sum_{s \in S} p(s) \cdot u(h(s))$$

- **The Evidence theory approach**

Evidence theory, also known as the theory of belief functions was developed by Shafer through Dempster's works. The transferable belief model [34,35] is a major contribution in the context of this theory. The Dempster-Shafer theory [36] can be seen as a generalization of probabilistic approach. The belief functions make it possible to take into consideration the principle of the open world. These functions can be used to manage multi-sources of information well and contribute to the assessment of the reliability regarding sources.

For each decision problem, the evidence theory defines a discernment domain $\Theta = \{A_1 \ldots A_n\}$ [37]. The power set 2^Θ contains the

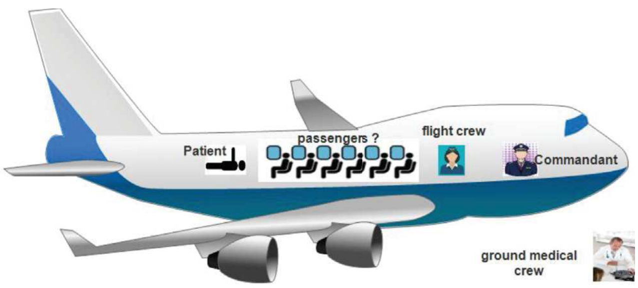

Fig. 3. Stakeholders of in-flight medical incident management.

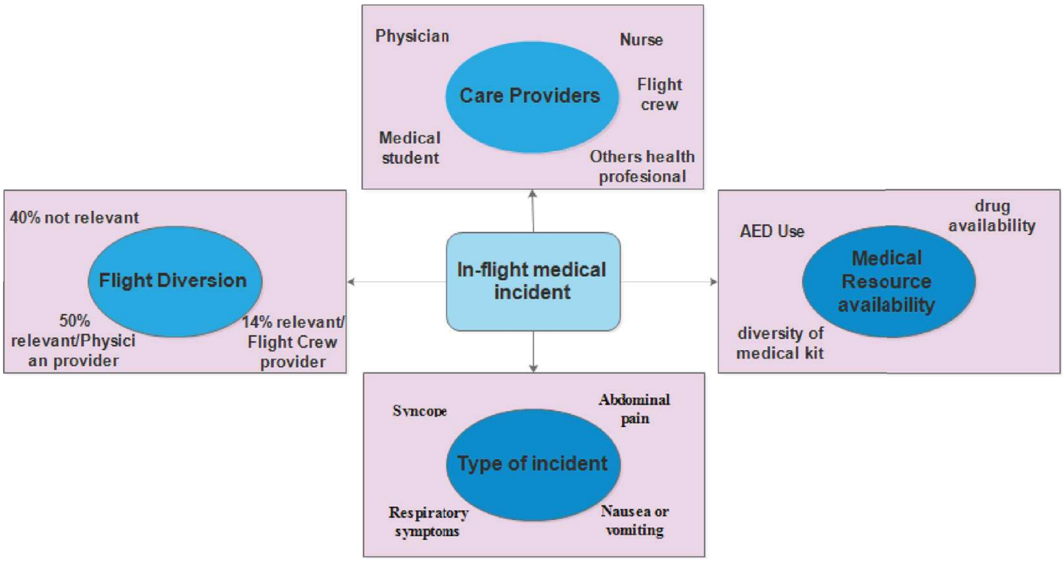

Fig. 4. In-flight medical incident characterization.

Table 2
Mapping studies variables and factors determining tolerance of uncertainty.

Variables	Type of factors
Incident category	Factors related to the patient
Missing Resource	Context of the medical care
Diversion	Clinical reasoning and risk estimation
Decision Maker (care provider)	Context of the medical care

set of possible decisions (set of all subsets of A and including the empty set). A belief mass *m* called basic belief assignment is assigned to each element of the power set. *m*(*A*) denotes the amount of evidence supporting the event A [38]. The function (m: $2^{\Theta} \rightarrow [0,1]$) follows the axioms:

$$m(\varnothing) = 0$$

The mass of the empty set is zero.

$$\sum_{A \subset \Theta} m(A) = 1$$

The sum of element masses is one.

$$bel(A) = \sum_{B \subset A,\ B \neq \varnothing} m(B)$$

Belief (bel(A)) can be interpreted as the total directly supporting the event A.

$$pl(A) = \sum_{A \cap B \neq \varnothing} m(B)$$

Plausibility (pl(A)) is the amount of evidence not contradicting the same conclusion.

Different rules are defined to combine two independent sets of beliefs in specific situations.

- The conjunctive combination
- The disjunctive combination
- Mixed combination

Another interesting aspect of belief functions is the complementarity they can have with data mining hence the next section named evidential data mining. They are often combined, because of their ability to model uncertain multiple sources of knowledge by the belief functions and the conflict management capability of data mining.

Table 3
An uncertain quantitative sequence database.

Transaction	Sequence	Probability
S1	< (a, 3), (b, 4), [(a, 1), (c, 1), (e, 2)] >	0.7
S2	< [(b, 1), (c, 1)], [(a, 1), (d, 1)], [(a, 2), (b, 2)] >	0.8

3.2. Evidential data mining

In this paper, data mining to build beliefs has been used. Regarding the nature of the in-flight incident studies, this option is more suitable. The relationships between care actions (medical action, aircraft diversion) and the factors determining the tolerance to uncertainty have been considered. Thus the modeling of the latter with belief functions will make it possible to act on uncertainty tolerance.

For Itemset mining in uncertain data [39,40], two main models are generally used, (1) the expected support model [41] (an itemset X is considered frequent if and only if its expected support is not less than a user-specified support threshold) and (2) the probabilistic frequentness model [42] (an itemset X is called frequent if the probability that X occurs in at least *minSup* transactions is above a given threshold). In the first approach, the basic idea consists in exploiting the statistical properties of those items with low existential probabilities with a framework that comprises three modules: the trimming module, pruning module and patch up module. In the second approach, it is adopted a dynamic programming technique for the efficient computation (using filter and pruning strategies) of probabilistic frequent itemsets.

Zang and its colleagues proposed a framework called High Utility-Probability Sequential Pattern Mining (HUPSPM) [40] that combines the idea of high-utility sequential pattern mining [15] with the expected support model. They use an uncertain quantitative sequence base (an example is shown in Table 3) and a profit table (an example is shown in Table 4). In this framework, an itemset is a set of items, where each item has a quantity and a probability.

Definitions: The utility of a sub-sequence S in a sequence S_q is the maximum utility among the utilities of all occurrences of S in the sequence. It is denoted as $su(S, S_q)$.

The probability that a sequence S appears in a sequence S_q ($S \subseteq S_q$) is denoted as $sp(S, S_q)$, where $sp(S_q, S) = sp(S_q)$.

The utility and probability of a sequence S in an uncertain quantitative sequence database abbreviated *USD* is defined as:

$$su(S) = \sum_{S \subseteq S_q \cdot S_q \in USD} su(S, S_q)$$

$$sp(S) = \sum_{S \subseteq S_q \cdot S_q \in USD} sp(S, S_q) = \sum_{S \subseteq S_q \cdot S_q \in USD} sp(S_q)$$

For instance, in Table 3, a sequence S = < (a), (b) > is contained in S1 and S2 where su(S, S1) = 3*2+4*1(=10) and su(S, S2) = 1*2+2*1(= 4) with sp(S, S1) = sp(S1) (= 0.6), sp(S, S2) = sp(S2) (= 0.8). Therefore, the utility and probability of S are determined as su(S) (= 10 + 4) (= 14) and sp(S) = sp(S, S1) + sp(S, S2) = sp(S1) + sp(S2) = 0.7 + 0.8 = 1.5, separately.

An approach extending the relational databases with Dempster-Shafer theory was proposed by Ref. [43]. It introduces the concept of an evidential database. Table 5 shows an example of an evidential transaction database.

Data mining notions (Item and itemset) are modified to support evidential values. Support notion is also modified to take into account belief mass. Tobji and his colleagues carried out a method to compute Itemset support [39].

Evidential Item: In an evidential transaction database the columns are attributes and the items are the focal elements corresponding to the attributes (Ex: SP, {SP, S}, MA).

Evidential Itemset: An itemset is a set of items corresponding to different columns (Ex: SP, D).

The support of an itemset X is its belief in the base (3, 4). It is calculated from the mass of the itemset (2). The mass of the itemset depends on the mass of the itemset in each transition (1).

$$m_j(X) = \prod\nolimits_{x_i \in X} m_{ji}(x_i) \quad j = transaction \quad i = attribut \tag{1}$$

$$m_{DB}(X) = \frac{1}{d}\sum_{j=1}^{d} m_j(X) \tag{2}$$

Table 4
Profit table.

Item	a	B	C	D	e
Profit	2	1	3	4	1

Table 5
Evidential data base, SP= Syncope-Pre-syncope; CS=Cardiac symptom; S= Seizures; RS = Respiratory symptom; MA = medical Action; D = Diversion.

Transaction	Type of incident	Action
T1	SP (0,5)	MA (0,6)
	CS (0,5)	D (0,6)
T2	{SP, S} (0,3)	MA (0,5)
	RS (0,7)	D (0,5)

$$Bel_{DB}(X) = \sum_{Y \subseteq X} m_{DB}(Y) \tag{3}$$

$$Support_{DB}(X) = Bel_{DB}(X) \tag{4}$$

In the ensuing section an evidential in-flight medical decision framework is described. Particular attention is being paid to CDSS which is the main component of this system, and plays a key role in the decision process.

4. An evidential in-flight medical decision framework

The methodological approach taken in this study is a mixed methodology based on knowledge engineering, evidence theory and data mining.

It is considered that the tolerance of uncertainty is related to the physician's ability to make decisions. Decision-making depends on the uncertainty level of the factors characterizing the patient's condition.

Fig. 5 shows an overview of CDSS architecture in interaction with the EHR. CDSS consists of a knowledge base, an inference engine and a communication system to collect and restore information to the user.

Fig. 6 presents the main components (knowledge base, inference engine and communications) involved in CDSS (Clinical Decision Support System (CDSS) that interacts with EHR (Electronic Health Records). Firstly, the theory of belief functions is used for uncertainty modeling, and the ontology is engaged to the semantic description of domain vocabularies and rules. Secondly, the care process was defined by formalizing the clinical pathway, which is transformed into a preference conditional base. Thirdly, after the construction of beliefs through data mining, inference engine and knowledge fusion tasks are defined. As a result, the constructed decision model is based on evidential itemset mining.

4.1. Ontology modeling

For the purpose of uncertainty representation, we use a generic ontology called Dempster-Shafer Ontology (abbreviated DS-Ontology) and developed by Ref. [18]. It provides the knowledge-structuring specification for instantiation of uncertain statements regarding any domain of knowledge.

4.1.1. Dempster-Shafer Ontology

The DS-Ontology is based on the formalism and Reasoning Process of the Dempster-Shafer Theory of Evidence and permits to manage uncertainties, inaccuracies and ignorance. This theory facilitates the combination of distinct evidence from various sources in order to determine a degree of belief integrating all the available hypotheses that are supposed to be exclusive.

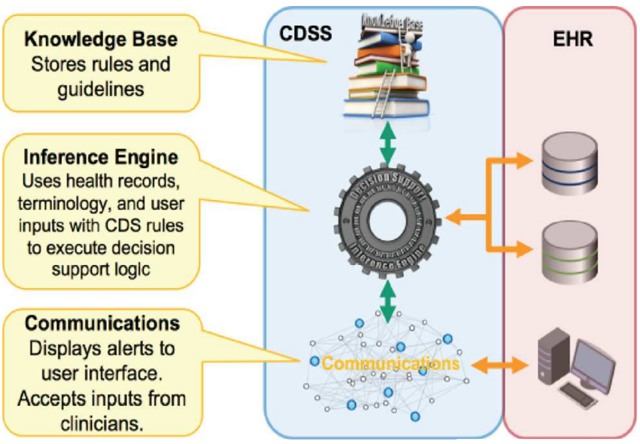

Fig. 5. Interaction between the CDSS and EHR.

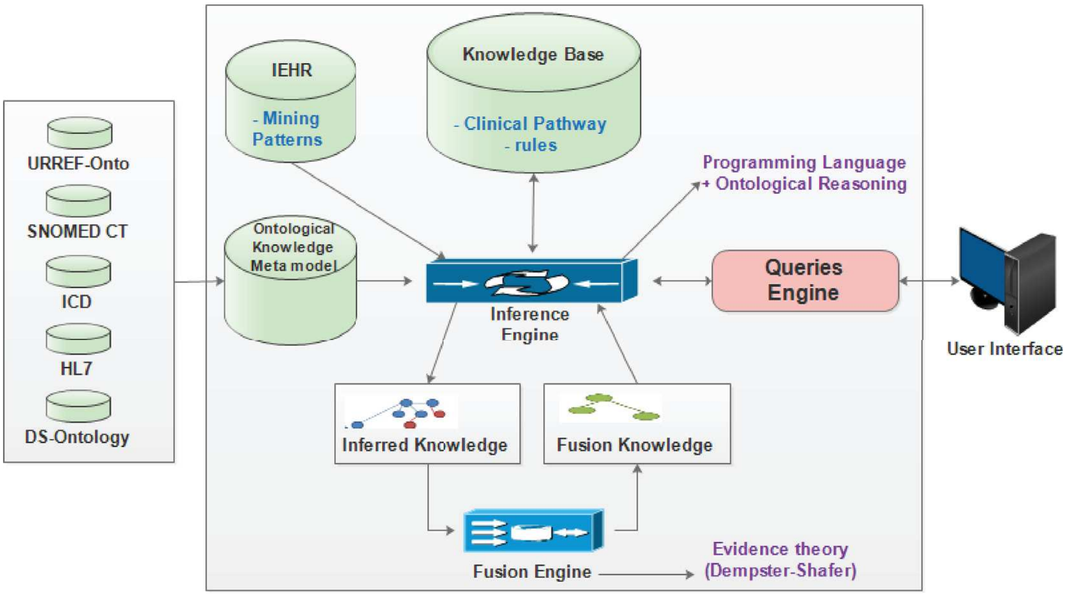

Fig. 6. An evidential in-flight medical decision framework architecture.

The DS-Ontology enables to characterize the degree of partial or full ignorance present in the sources by assigning degrees of belief to high-level abstract ontological concepts. The DSOntology can be combined with any domain ontology in order to ensure its instantiation in an uncertain manner (Fig. 7).

The characterization of uncertainty is flexible and easy. Since uncertainty is represented using belief functions, any concept with an uncertain aspect is a DS concept (hasDS_concept). The hypotheses are related to the domain of discernment through *the hasDS_hypothesisElement* relation. Each uncertain DS_concept has four datatype properties: *DS_source*, *DS_mass*, *DS_belief* and *DS_plausibility*.

4.1.2. Domain-task ontology

Fig. 8 shows 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 to be addressed. These problems are solved through actions that require resources. Actions produce results through the expected outcomes.

For syntactic and semantic interoperability, medical terminologies such as SNOMED CT, ICD, HL7 [44,45] can be imported. In addition, it is also possible to use ontologies that contain concepts related to the study of uncertainty such as the Uncertainty Representation and Reasoning Evaluation Framework (URREF) designed for the Evaluation of Techniques for Uncertainty Reasoning [46].

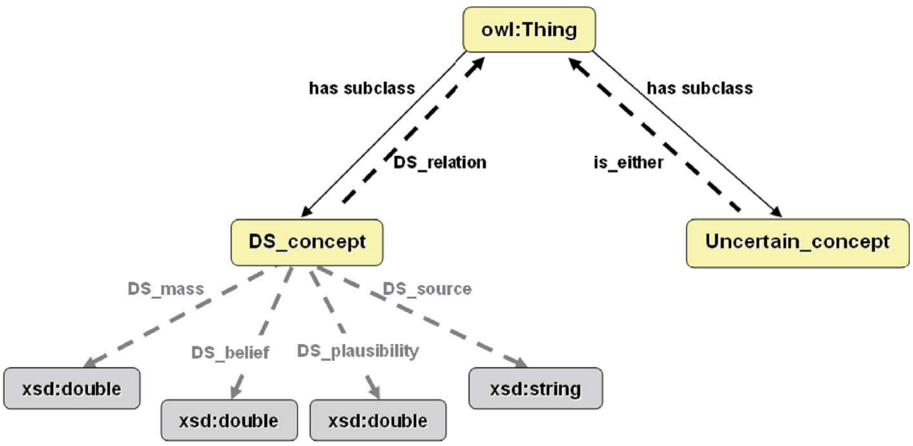

Fig. 7. DS-ontology structure.

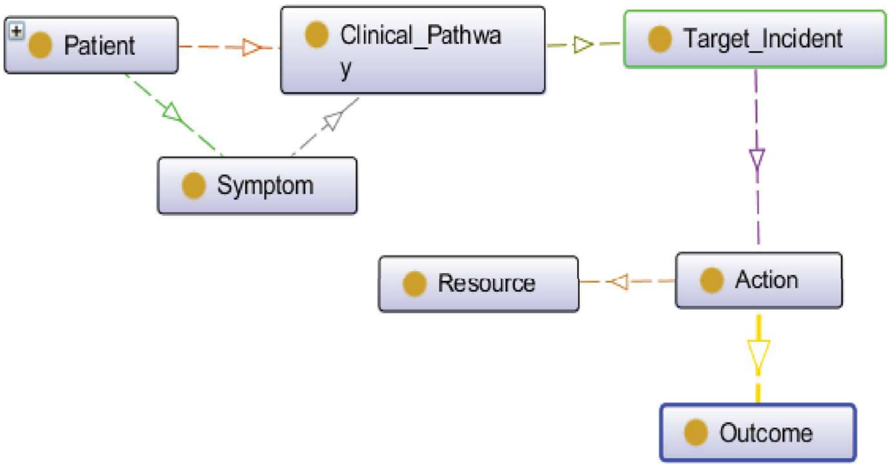

Fig. 8. Characterization of in-flight medical environment.

4.1.3. *Uncertainty concept*

Many discernment domains as variables determining in-flight medical assistance have been defined in this section. Indeed, uncertainty concerns the actions, the type of incident (Clinical Pathway), and lack of resources, which makes them uncertain concepts (DS concept).

$$\Theta_1 = \{CP_1,\ CP_2,\ CP_3,\ CP_4,\ ...\}$$

$$\Theta_3 = \{A_1,\ A_2,\ A_3,\ A_4,\ ...\}$$

The *hasDS_hypothesisElement* relationship (DS_concept, In-flight_charact) makes each instance of the In-flight_charact concept an uncertain event with mass, credibility, plausibility, and a source.

4.1.4. *A Conditional Preferences Base approach to formalize clinical pathway*

The considered decision process uses the Clinical Pathway composed of targets. Each target defines a set of actions and for each action its beginning, duration and periodicity (Table 6). So a Clinical Pathway is a succession of actions, each with its own inputs, preconditions, outputs and outcomes (Fig. 9). Medical actions may have dependencies between them. These dependencies are modeled by preferences, which make it possible to integrate the action “Diversion".

Clinical Pathway 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 [47], 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 the interdisciplinary team; (2) focused on the quality and coordination of care” [48]. Clinical Pathways are almost always 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 fits into collaborative processes [49], which makes it interesting for the application of telemedicine.

Another aspect which reinforces the choice of the Clinical Pathway is the selection of the granularity (level of detail) for a description 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 [50]. There are some CDSS that propose care procedures (admission, surgery and discharge) [51], but they are not suitable for in-flight medical incident management.

A conditional preference base is a triple PB = (T, A, P) where T is a knowledge base, A is a finite set of concepts, and P is a finite

Table 6
Clinical Pathway consists of targets (observations).

Clinical Pathway		
Target 1	Action 1	Begin, duration, period
	Action 2	Begin, duration, period
	Action 3	Begin, duration, period
Target 2	Action 2	Begin, duration, period
	Action 4	Begin, duration, period
…		

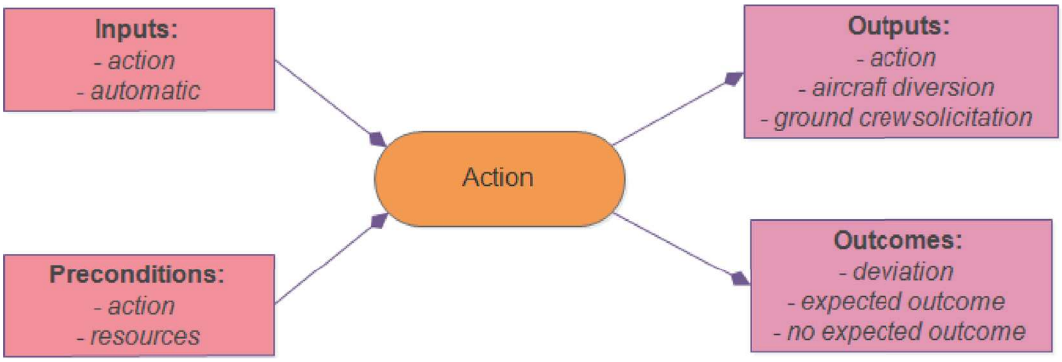

Fig. 9. Structured analysis of the links between actions.

set of conditional preference [52].

A conditional preference is of the form (α|φ)[s], where α and φ are concepts (called its head and its body, respectively), and s is an integer (called its strength).

In contrast to [52]; this can be done without the power s, the conditional preference becomes (α|φ). (α|φ) expresses that generally, among the objects satisfying φ, the ones satisfying α are preferred over those satisfying ¬ α.

Intuitively, conditional preference bases PB = (T, A, P) encode rankings on a set of individuals o. Here, intuitively, T represents background knowledge, and A represents assertional knowledge about each o.

Knowledge Base

$$
\begin{aligned}
T = \{&ValidAction \subset \mathrm{Outcome};\\
&ValidAction \subset \mathrm{Outcome};\\
&DSconcept \subset DSClass;\\
&follow(Patien,\ ClinicalPathway);\\
&actionInputs(Action,\ Action);\\
&actionPrecondition(Action,\ Resource);\\
&actionOutputss(Action,\ Action);\\
&precede(Action,\ Action);\\
&contains(Clinical\ Pathway,\ Action);\\
&contains(hasDShypothesisElement\ (DSconcept,\ Action))\\
&...\}
\end{aligned}
$$

Uncertainty concept

A= ClinicalPathway, Action, Patientscondition

Conditional preferences:

The following formula defines the form of our conditional preferences.

$$\mathop{\mathrm{U}}_{Action\ \in CP} Inputs\ \cap \neg ValidAction \,\Big|\, Action$$

This means among the objects satisfying Action, we preferred the ones which are inputs and not yet been validated. One defines the scheduling of actions because this relation is also transitive. This relation is materialized by the property “precede” in the ontology.

The specification of an action is done in the section inference engine (4.1.3).

Let us look for example the case of a “Paediatric Acute Gastroenteritis” [53]. The actions to take care of such a case are to:

- Continue feeding (CF)
- Give extra fluids (EF)
- Tell when to return (TWR)
- Give zinc supplements (ZS)
- Give Oral rehydration solution 75 ml/kg over 4 h (ORS)
- Give intravenous fluids 100 ml/kg Ringer's lactate (preferred) or normal saline (IVF).

The conditional preference base will consist of the following elements:

EF ← CF; CF ← TWR; TWR ← ZS; ZS ← ORS; ORS ← IVF

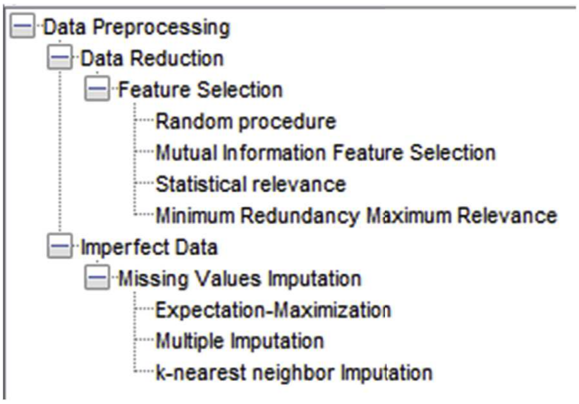

Fig. 10. Pre-processing of data for high-utility itemset mining.

4.2. *In-flight Electronic Health Records (IEHR)*

The IEHR contains an evidential transaction database. It was built in two stages. We first looked for any relationship between two factors determining the in-flight medical management (type of incident, diversion, absence of medical equipment …) supported by classic data mining. These relations correspond to the associative rules. An associative rule [54] is a causal relation of the form r: A → B. A (premise) and B (conclusion) are itemsets. The items are therefore types of incidents, used resources, missing resources and diversions. This work, which will not be described in detail in this article, was carried out using SPMF (Open-Source Data Mining Library [55].

Firstly, we implement the "FPGrowth_association_rules" algorithm and required a preprocessing work whose steps are visible in Fig. 10. It is noted that in this work, we always have as premises the occurrence of an incident (Incident → Type of incident, Incident → Action). Particularly, because of the lack of structuring of the data some relationships were extracted directly from the text. FP Growth_association_rules algorithm searches all association rules following the two steps approach proposed by Ref. [56]. The first step is to discover frequent itemsets. The second step is to generate rules by using frequent itemsets. Instead of the Apriori algorithm used in the first step by Ref. [56]; this implementation operates with the FP Growth algorithm [57] using a special internal tree structure permitted for improving the operational efficiency and scalability to mine both long and short frequent patterns.

Secondly, we transform the conclusions of each rule into a discernment or inference domain. The variables determining the management of medical incidents become uncertainty concepts; which is normal since they are also the determinants of tolerance to the uncertainty. In this way, an evidential base of transitions is constructed [39,58].

Fig. 10 shows the data pre-processing used for data mining. This pre-processing includes data reduction with feature selection (i.e. choosing a subset of relevant features) and imperfect data management with missing values imputation (i.e. data that has not been

Table 7
In-flight evidential items.

Id	Type of incident	Action	Provider	AED Use
IEHR	• Syncope or pre-syncope: SP • Respiratory symptoms: RS • Nausea or vomiting: NV • Cardiac symptoms: CS • Seizures: S • Abdominal pain: AP • Infectious disease: ID • Agitation or psychiatric symptoms: APS • Allergic reaction: AR • Possible stroke: PS • Trauma, not otherwise specified: T • Diabetic complication: DC • Headache: H • Arm or leg pain or injury: ALP • Obstetrical or gynecological symptoms: OG • Ear pain: EP • Cardiac arrest: CA • Laceration: L • Other: O • Unknown: U	• Diversion: DD • Emergency Medical Service request: EMS • Medical Action: MA	• Physician: PP • Nurses: PN • EMS: PEMS • Other Health care professionals: PO • In-flight Crew: PIC	• AED use for syncope: AEDS • AED use for Chest Pain: AEDC • AED use for other: AEDO • AED not use: AEDN

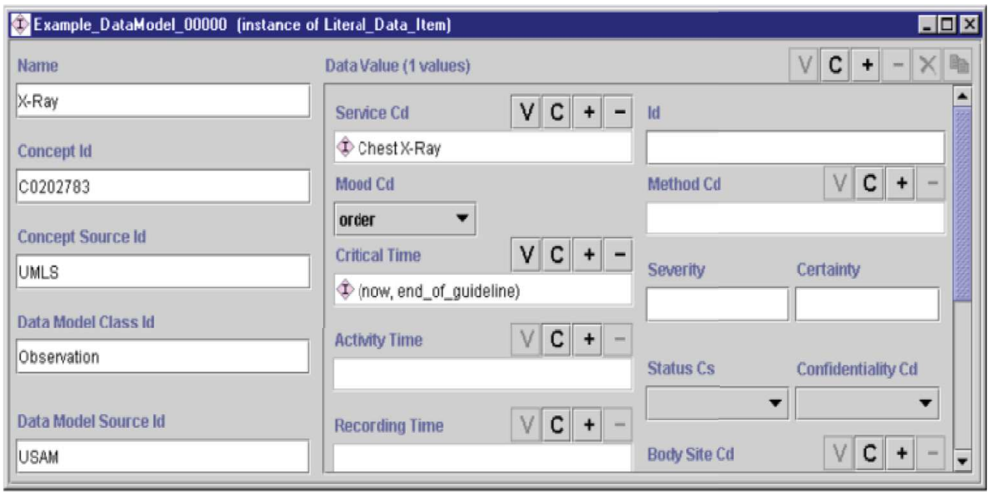

Fig. 11. Illustration of a clinical action.

stored or gathered).

Table 7 shows a set of evidential items corresponding to determinants of medical management [25]. There are four discernment domains (types of incidents, action, profiles of the decision maker and use of the automated external defibrillator (AED)).

4.3. *Inference engine*

Inference engine is an important component in CDSS, and plays a key role in the medical decision process. It collects users' needs, accesses to IEHR, activates the knowledge fusion system and defines the reasoning. The inference engine combines ontological reasoning and computer programs.

Actions in the clinical pathway specify two types of tasks [59], (1) medical nature (clinical action) or (2) system task (performed by the inference engine).

4.3.1. *Clinical action*

Clinical actions represent medical terms and concepts. Fig. 11 shows an action prescribing a chest radiograph. These actions represent CDSS outputs.

4.3.2. *System actions*

System actions characterize the inference engine and can be organized as an algorithm. We wanted a typology of system actions that even by reducing the complexity of representation in tools like GLIF, HL7 and ISO 13606 [60] always remains compatible with these standards for interoperability issues [61].

Our inference engine implements 7 actions:

- **Get User Action**: this action recovers the wish of the user.
- **Set Fusion Action**: This action calls « fusion engine ».
- **Get beliefs**: it gets back decision-maker beliefs.
- **Get Current Medical Action**: get back the action to be performed according to the clinical pathway.
- **Resource Available Action**: it checks if the resources necessary for the execution of a medical action are available.
- **Visualization Action**: it visualizes the medical action
- **Visualization beliefs**: it visualizes beliefs.

4.3.3. *Decision-making process*

Fig. 12 shows the decision-making process algorithm.

In this study, the notion of high utility itemsets to act on the decision maker's uncertainty threshold (Fig. 13) has been used. It is built a transaction corresponding to the beliefs of the decision maker. If he wants to perform a medial action and the necessary resources are available, the action is visualized. Otherwise one adds one's beliefs to the transaction base and one calculates the supports of all High Utility Itemsets. For this purpose, we use the method of [39]; taking into account also the fact that according to Air France, a diversion proposed by the Emergency Medical Services (EMS) is relevant in 85% of cases, compared to 50% when proposed by a passenger medical doctor and only 14% when a crew member proposes it. Furthermore, on overall, a posteriori, 40% of the diversions proved unjustified [10]. To do this end, we update the transactions with the *UpdateTransactionBase* algorithm (Fig. 14).

The *UpdateTransactionBase* algorithm takes as input a table which contains for each transaction that needs to be modified a

```
def Get_beliefs()
def Set_Fusion_Action(beliefs)
def Get_Current_Medical_Action()
def resource_Avalable_Action(medical_action)
def Visualisation_Action(action)
def Visualisation_beliefs(beliefs)

def in_flight_medical_decision:
    action = Get_Current_Medical_Action()
    if Get_beliefs().'AM'==1 & resource_Avalable_Action(action)== True:
        Visualisation_Action(action)
    else:
        beliefs = Get_beliefs()
        Set_Fusion_Action(beliefs)
        Visualisation_beliefs(beliefs)
```

Fig. 12. Decision-making process algorithm.

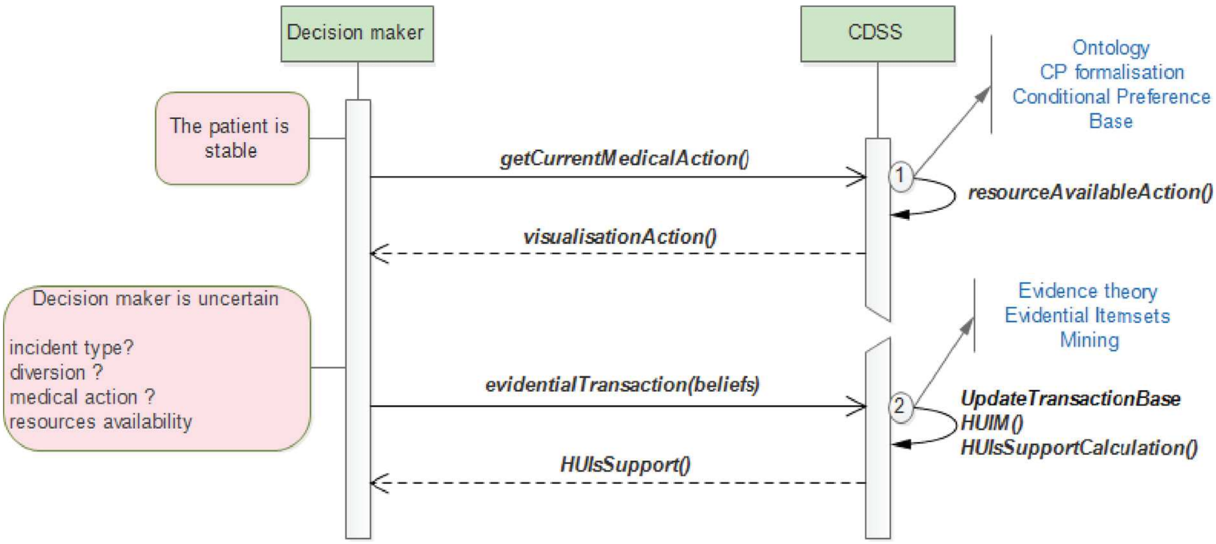

Fig. 13. CDSS interactions (action execution process).

def $UpdateTransactionBase\ (weightTable)$:

$\quad \#weightTable = \{\ (item_1, weightItem_1, t_1), (item_2, weightItem_2, t_2), \ldots\}$

$\quad for\ each\ line\ (item, weightItem, t)\ in\ weightTable$:

$\quad\quad for\ each\ cell_{ta}:\qquad \#\ a\ is\ an\ attribut$

$\quad\quad\quad if\ item \in cell_{ta}$:

$\quad\quad\quad\quad m_{ta}(item) = m_{ta}(item) - weightItem * m_{ta}(item)$

$\quad\quad\quad\quad m_{ta}(it) = m_{ta}(it) + weightItem * m_{ta}(item), \quad it \in cell_{ta}$

Fig. 14. *UpdateTransactionBase* algorithm.

'change factor' and the item concerned. A simplified description of this algorithm is given below.

Let be $weightTable = \{(item_1,\ weightItem_1,\ t_1), (item_2,\ weightItem_2, t_2), \ldots\}$ this input.

t_1, t_2, ... transactions that need change

$item_1$, $item_2$, ... concerned items

$weightitem_1$, $weightiemt_2$, ... change factor for each item

1 For each line $(item,\ weightItem,\ t)$ in weightTable do
   a. For each cell in transaction t do
      i. If item is in the cell
         1. Update cell

4.4. Fusion engine

As discussed in Section 4.3.3, we use the method proposed by Ref. [39] and the *UpdateTransactionBase* algorithm to combine the decision maker's beliefs with knowledge in the IEHR. This combination is actually a HUI support calculation. The objective here is to calculate the support of itemsets that can improve the decision maker's uncertainty tolerance.

Unlike in the HUPSPM framework [40], the utility of our itemsets is not quantitative. It is the decision maker uncertainty who defines it. We consider as itemset with high utility any itemset in Cartesian product of discernment domains in decision-maker transaction. HUIs are a set $(o_1,\ o_2,\ \ldots)$ where $o_1 \in \Theta_1, o_2 \in \Theta_2$, ... They represent the possibilities describing the state of the world.

$$HUI_s = \prod_{x_i \in DMT} x_i$$

DMT = Decision Maker Transaction

The number of HUIs depends on the cardinality of each discernment domain in the decision maker's transaction. The more uncertain it is, the more HUIs there are.

The following is a simplified description of our HUIM algorithm.

1 Let T an evidential data base, $T_{DM} \in T$ a transaction containing decision maker beliefs.
2 Update T if necessary (Fig. 14)
3 Use $T_{DM} \in T$ to determine HUIs (4.1.4)
4- For each HUI
   a. Determine the mass of the all transactions (3.1)
   b. Execute Support (Belief) calculation (3.1)

The first step allows us to update the database with data subsequent to its creation or from other studies. The update algorithm provides some scalability and flexibility to the system. In the second step, the use of the Cartesian product is necessary to take into account all the uncertainty of the decision-maker. The complexity that can be generated by using this operation is reduced by the number of variables to be combined. In the third step, we use the support of the HUIs which is in the form of belief mass and which can therefore be considered to be well suited for the enrichment of decision-making processes.

Table 8 presents the experimental data [25] on in-flight medical assistance under uncertainty. The first line contains In-flight Electronics Medical Records in the form of evidential transaction. The second line shows decision makers' beliefs. With such data $HUI_s = \{X,\ Y\}$.

Table 8
In-flight evidential transaction base (source [25]).

Id	Type of incident	Diversion	Provider	AED Use
IEHR	SP (0,374) RS (0,121) NV (0,095) CS (0,077) S (0,058) AP (0,041) ID (0,028) APS (0,024) AR (0,022) PS (0,02) T (0,018) DC (0,016) H (0,01) ALP (0,01) OG (0,005) EP (0,004) CA (0,003) L (0,003) O (0,069) U (0,01)	DD (0,073) {EMS, MA} (0,927)	PP (0,481) PN (0,201) PEMS (0,044) PO (0,037) IC (0,237)	AEDS (0,00533) AEDC (0,003107) AEDO (0,004563) AEDN (0,987)
Decision maker	SP (1)	DD (0,5) {EMS, MA} (0,5)	PP (1)	AEDN (1)

Table 9
An illustration of an *UpdateTransaction* Base.

Items	Weight of Items	Transaction
DD	0,5	Decision maker
DD	0,4	IEHR

- X = SP-{EMS, MA}-PP- AEDN denotes the management of a type syncope incident by a physician in the absence of a defibrillator and without diversion, and
- Y = SP-DD-PP- AEDN where the physician requests a diversion.

We have two HUIs because the decision maker's uncertainty concerns only flight diversion.

In-flight medical incidents, the principle of using domain knowledge of the data to generate features (i.e. feature engineering) provides the input of the *UpdateTransactionBase* algorithm (Table 9). Data from other studies show that 40% of diversions are irrelevant [10]. To take this into account, the IEHR transaction is updated. It is also known that if the volunteer is a physician, 50% of the diversion is irrelevant, requiring an update of the "decision maker" transaction. The item DD denotes the request for a diversion. In Table 9, it is illustrated an *UpdateTransaction* Base with 50% of irrelevant diversion suggested by the decision maker and 40% of irrelevant diversion recorded in the IEHR and suggested by physician provider.

UpdateTransactionBase produces the final evidential transaction base (Table 10) on which formulas (1), (2), (3), (4) are applied in order to determine the support of each HUI.

$Support(X) = Bel(X) = 0{,}46$ and $Support(Y) = Bel(Y) = 0{,}129$

5. Discussion

The proposed research approach is part of the design and organization of an in-flight medical decision system under uncertainty. In addition to considering the adequacy of the information managed, we have formalized the Clinical Pathway into conditional preferences, thus creating a care process. We have extended the notion of evidential transaction base by proposing an algorithm to correct beliefs. We dealt with the determining factors behind the in-flight medical assistance, which are also determinants of tolerance for the inherent uncertainty of the medical decision process.

The use of ontologies is interesting, since this brings more rigors in the analysis and provides enhanced results relative to data structures and information representations. For instance, it is possible to specify the underlying semantics in order to identify common elements and missing links within the data of in-flight medical incidents. As a method of knowledge engineering, ontology offers symbolic reasoning powers combined with numerical reasoning of data mining fostering a co-evolution process that enriches information extraction and knowledge discovery.

Compared to health economic theory and methods, we can intervene in decision making processes in an uncertain and critical

Table 10
In-flight evidential transaction base updated.

Id	Type of incident	Diversion	Provider	AED Use
IEHR	SP (0,374) RS (0,121) NV (0,095) CS (0,077) S (0,058) AP (0,041) ID (0,028) APS (0,024) AR (0,022) PS (0,02) T (0,018) DC (0,016) H (0,01) ALP (0,01) OG (0,005) EP (0,004) CA (0,003) L (0,003) O (0,069) U (0,01)	DD (0,0438) {EMS, MA} (0,9562)	PP (0,481) PN (0,201) PEMS (0,044) PO (0,037) IC (0,237)	AEDS (0,00533) AEDC (0,003107) AEDO (0,004563) AEDN (0,987)
Decision maker	SP (1)	DD (0,25) {EMS, MA} (0,75)	PP (1)	AEDN (1)

Table 11
Decisional-making matrix.

	Stable state	Worse state	Critical state
Type of incident	Type of incident (Stable state)	Type of incident ()	Type of incident (Critical state)
Diversion	Diversion (Stable state)	Diversion (Worse state)	Diversion (Stable state)
Provider	Provider (Stable state)	Provider (Worse state)	Provider (Stable state)
AED Use	AEDUse (Stable state)	AED Use (Worse state)	AED Use (Stable state)

environment by selecting the suitable level of granularity. Our medical actions are not only "Treatment" or "No treatment" but they cover all relevant medical acts defined in the considered care process. Thus a key component of this study focuses on the notion of Expected Utility, which is used to extract information that can be helpful in developing the reasoning process, thus maximizing the expected utility of a medical action.

The complexity of implementation is also considerably reduced. Indeed, if one was to use such methods, it is necessary in addition to the discernment domains to define the states of the world. In our case it could be the patient's condition. Then we must determine the utility of each action in each state of the world (Table 11).

There are some open questions that merit further consideration and investigation, such as those concerning the computational complexity and the itemset support management. As regards the complexity of itemsets mining, the transaction base design can be carried out upstream. In the considered application, the IEHR contains only one transaction. However, the calculation time depends on several factors of the HUIs. Two mathematical operations that return a set of multiple sets (called Cartesian products) are made during the decision process. The use of the Cartesian product is not the only thing we need to improve; our system uses itemset support to assist the decision-making. The confidence that introduces conditionality (in the case of basic evidential transactions) can help to improve the analysis supporting the decision-making under uncertainty. Finally, a SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis is developed in Table 12.

6. Conclusion and future works

This study proposes an evidential in-flight medical decision framework to manage medical uncertainty. This method is based on evidence theory, data mining and ontologies. A significant feature engineering work was needed to identify in-flight medical uncertainty.

The ontologies provide a method for knowledge formalization, modeling and structuring. Demster-Shafer's theory and the HUI mining allow us to consider all the uncertainty of the decision-making process and to estimate the specific conditions of a high-risk situation.

Our decision system implements a high-utility itemset mining algorithm in context of evidential transaction base. This facilitates the end-user uncertainty expression, and allows the construction of medical action utilities. We introduced a new way of considering and calculating this utility and created a database maintenance algorithm.

Analyses of historical data and other experienced sources will enrich the pool of information and knowledge that is necessary for enlightened critical decisions. The high-utility itemset mining allows finding the itemsets (group of items) that generate a high benefit in the target database. In our case, this benefit is related to a better management of in-flight medical incidents.

These analyses also include a more comprehensive assessment of health needs and taking more account of the possible uncertain situations with problems relating to the inherent uncertainty of the critical decision-making process. Consideration of the accepted tolerance threshold for the presence of uncertainties in the decision-making process therefore seems unavoidable.

In this work we proposed a computerized approach to support critical decision-making processes and contribute to providing suitable medical care for in-flight medical incidents. These decision-making processes are complex with external and internal uncertainties pertaining to the sick passenger, airline policy, air traffic management and remote communication procedures. So, there are several variables (e.g. incident type, medical action, accessible diversion options and available resources) that need to be considered in order for both scientific and pragmatic considerations, with regard to the health of airline passengers.

Nevertheless, the legal basis for the emergency assistance in in-flight medical incidents is often weak or variable across countries, frustrating volunteer doctors at the lack of sufficient information and clear knowledge. Even so, lack of full legal and scientific certainty should not prevent the proposal of possible solutions for meeting the critical medical needs of the passengers in air travel.

Table 12
A SWOT analysis.

Strengths	Weaknesses	Opportunities	Threats
A flexible framework for the knowledge extraction from in-flight databases. Uncertain ontology modeling and evidential data mining through the Dempster-Shafer Theory of Evidence.	The computational complexity of itemsets mining. The semantic intersection and inclusion of conceptual instances.	Decision making support system for improved care of passengers in air transport. Reasoning with limited data available having a low quality or quantity.	The legal or contractual restrictions and considerations. The divergent political and medical arguments.

In a short-term perspective, we will examine the detection of clusters and taxonomic relations among the varied selection of categorized items (e.g. using a fast minimum spanning tree algorithm [71]. This, in turn, can offer an opportunity to define schemes to provide a better analysis of the most important and influential relationships between items of the same and different categories.

In a medium-term perspective, we will improve the decision mode [62–64] which is currently based on the HUI support calculation. Additional features engineering cycle (e.g. selection, prioritization and transformation of features representing the problem and its input data) is also needed to improve the proposed model. Likewise, ontology-based deep learning [65] is an emergent topic for human behavior prediction with explanations and this could contribute to ease domain-specific knowledge representation or argumentations [66–70] and facilitate emergency efficiency during critical medical interventions in the air transport for the safety of their passengers.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.datak.2018.06.002.

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