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Using cluster analysis to identify weak signals of lethal trends in aviation and healthcare documentation

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Abstract: Effective methods are needed to identify and manage risks in both aviation and healthcare to improve safety. Analysing safety related records and learning from 'touch and go' situations is one possible way of preventing hazardous conditions from occurring in both aviation and healthcare. The eventuality of an incident or an accident may markedly be reduced if the risks connected to it are efficiently diagnosed. With the aid of this outlook, flight safety has witnessed decades of successful improvement. Since aviation and healthcare share similarities, the methods for improving safety could be transferable between the domains. This paper explores how a data mining technique used in aviation to identify the weak signals of lethal trends can be applied to healthcare documentation.

Keywords: aviation safety; patient safety; lethal trend; hazardous event; healthcare; aviation; risk management; text mining; clustering; weak signal.

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1 Introduction

Air transport is today seen as the safest mode of transportation. Its current level of safety is the result of a huge amount of systematic work, the foundation of which was laid as early as the middle of the 1940s. Since the end of the 1950s and the beginning of the 1960s, the aviation accident rate has been greatly reduced due to this safety work (TraFi, 2011). When aviation technology reached a sufficient degree of maturity, the moving of the focus of the exploration of aviation safety to the analysis of human error was enabled. In addition, checklists and standard operating procedures were systematically taken into use. One essential detail to be added to the list is the development of decision-making aids, such as fault situation instructions (Sorsa, 2012). Healthcare could potentially gain from adopting and integrating many important tasks that are used in aviation to reduce errors and to standardise processes as methods for risk identification, analysis, and management, especially as such processes are more advanced in aviation than in healthcare (Pronovost et al., 2009).

Safety issues have received increasing attention in healthcare in recent years. Practice guidelines and safety protocols have been announced in order to reduce harm to the patient. The need for an increase in healthcare safety practices is emphasised by Whitehurst et al. (2012), who show that errors, which could have been prevented, may have resulted in the suffering of patients, permanent disability and even death. Death can be caused by medical errors that result from a lack of formal data schemas for presenting the structured data of voluntarily reported events. Therefore, both standardised, codified aggregate data and its thorough examination – using methods for the close analysis of fine-grained detail – is required in order to identify hazardous events accurately and consistently (Whitehurst et al., 2012), thus preventing individual hazardous events from recurring and creating lethal trends.

Potentially hazardous events do not necessarily result in accidents as they may be spotted and prevented. This observation is applicable in different contexts like aviation, healthcare, the nuclear industry, etc. Disasters, as well as accidents and serious incidents, do not just happen; they are a chain of critical events. These critical events can be illustrated through Reason's Swiss cheese model (Reason, 1997), a theoretical tool for analysing the development and outcome of lethal trends. In the model, defensive layers protect potential victims from local hazards that would otherwise continue their way through the cheese and result in an accident (Reason, 2000). In the model five defensive layers are divided into latent and active failures. The defensive layers may depend on technology or they may rely on people. Studying the weaknesses in the defensive layers helps to analyse possible lethal trends and manage risks proactively. It is widely recognised that about 80 per cent of the information that flight safety reports contain is in their narrative parts (Kloptchenko, 2003; PolyVista Inc., 2012). The latest studies on aviation suggest that text mining can be utilised to detect these trends (Sjöblom, 2010), i.e., the chains of events that lead to accidents if intervention does not occur (Reason, 2000). This paper aims to explore how a data mining technique that is used in aviation to identify the weak signals of lethal trends can be applied to healthcare documentation.

2 Safety aspects in aviation and healthcare

Safety is a core issue in the airline industry and in healthcare. During the first 50 years of aviation the technology was so challenging that it did not leave much space for other concerns (Sorsa, 2012). Since then, the global change in safety development has been similar, regardless of the location, at least among developed countries as well as in different types of aviation, like sport (TraFi, 2011) and military aviation resources (Koho, 2005). Today, the almost 200 member States of ICAO systematically focus on regulations and policies that consistently improve the safety, security and environmental sustainability of air traffic (ICAO, 2010). Safety is not a matter-of-course, but the result of a rather complicated management process. The determination of an acceptable level of safety is based on performance measurement, including defined safety performance indicators and targets, which are implemented through various safety requirements under the commitment of accountable and responsible management (Hsu et al., 2010).

Several components are needed to create a good safety culture in an organisation when using a continuous process that has monitoring and feedback as focal elements – and which will include standards, norms and strategy and policy (McDonald, et al., 2000). Organisational factors were not taken into account in aviation safety thinking until the 1990s. Furthermore, the evolutionary development of the technical and human factors were not successive but complementary and their appearance in the field come about in steps (ICAO, 2009). The reporting and investigation of all kinds of safety related events in aviation was defined in Annex 13 to the Chicago Convention in 1944 (ICAO, 2004). The annexes are updated frequently (Oritz and Capaldo, 2004) to correspond to the contemporary requirements of the operating environment. Annex 13 minutely sets out the rules on the notification, investigation and reporting of accidents, defines the rights and duties of the different parties to an accident, orders how investigations will be conducted and how the final results will be reported. The focal point of the annex is to prevent accidents and incidents through investigation, not apportion blame or liability (ICAO, 2001).

Defining the concepts ‘patient safety’ and ‘care quality’ is not simple because the boundary between the two concepts is indefinite, despite the growing amount of literature on the subject. Quality can be separated from safety as an increase in quality does not necessarily result in safer care (Sheps and Cardiff, 2011). Yet, the concepts have many, even overlapping definitions (Boaden, 2006), and they may be approached from different perspectives, but generally we talk about the same phenomena – care cannot be high quality unless it is safe (Moss and Barach, 2002). The definition of patient safety according to the World Health Organization (2013) is “absence of preventable harm to a patient during the process of health care”. The subject area of patient safety has become an important issue during the past two decades. Similarly to aviation, healthcare errors may result in serious harm and even lead to death. Adverse events in health can lead to several serious consequences and it has been estimated that nearly 100,000 patients in the USA die each year from medical errors, making medical errors the fifth leading cause of death in the USA (Kohn et al., 2000). Similar development has been noted in other western countries and it has been estimated that one person in ten is harmed while receiving healthcare, even though that harm was preventable (World Health Organization, 2013).

According to Prior (2011) organisational failures do not happen factually on the organisational level but their origin is in individual acts. Consequently, safety performance is based on individual engagement and activity. Regarding the just culture, it supports flight safety by laying strong foundations. In just culture, risk transparency is brought into daily thinking (Prior, 2011). In accordance with the just aviation safety culture, the safety procedures set the basic requirements for safety during professional flight operations, i.e., the agreed operating models create an aviation safety net. At best, the procedures are written in manuals and tell plane crews all the exact procedures, many hundreds of them, and present their accurate timing in the corresponding situations that could occur during a flight (Otelli, 2010). Other well-tried (and often obvious) things, like good airmanship, i.e., established practices promoting safe flying, can also be classed amongst them. Standard operating procedures are a strong defence against deviations and errors that can cause harm in the aviation industry. The procedures are continuously refined on the basis of the information produced by processes of analysis.

Care quality research is mostly conducted in developed countries and there is growing evidence of poor health outcomes due to unsafe healthcare in transitional and developing countries too. Even though medical care can cure diseases, it can also cause preventable suffering and harm (Jha et al., 2010). The Institute of Medicine underlined the need to make patient safety a major priority for healthcare authorities in the late 1990s and the pressure to increase patient safety has continuously been an issue (Kohn et al., 2000). The improvement of quality in patient safety work among healthcare providers, researchers, administrators and policy makers has been of growing interest ever since.

Compared with other high risk industries, such as aviation, healthcare still lags behind in its development and use of an incident reporting system. However, healthcare has utilised incident and near-miss-reporting and it has become an important part of patient safety improvement work. Reporting near-misses and incidents helps to identify problems in patient safety (Giles et al., 2006). Incident reporting alone cannot make care safer but the response to the reports can. Healthcare shares many features with aviation: high safety standards, the importance of communication, multidisciplinary teams, a stressful working environment and high requirements regarding skills and technology (Amalberti et al., 2005; Reader and Cuthbertson, 2011). When an error has been detected in aviation, corrective procedures follow. This should also be the case in healthcare as the question is ultimately always about individuals. Each story of failure ends with a real person with a real story (Department of Health, 2005). Both sectors belong to the so-called high-risk or safety critical industries, among which the concept of safety culture is essential.

The quantitative assessment of risk in aviation safety is particularly challenging because serious deviation events are extremely rare and the causal factors are non-linearly related to events, which makes them difficult to quantify (Hadjimichael, 2009). However, air traffic is full of incidents and deviations that do not contain any hazard as such, but need to be investigated to find out potential lethal trends. As an illustrative and relatively frequent example, incidents where a standard safe separation is slightly violated can be mentioned. These undesirable, but very minor events provide valuable investigation cases that enable risk and safety specialists to build their understanding of the causes of lethal trends and how to detect lethal trends. Investigation reveals whether countermeasures are warranted and how to reduce or eliminate potential accidents (Kirwan, 2011).

Heinrich (2007) defines latent threats as risk increasing factors residing in the system, such as flawed procedures, defective communications, inspection shortcoming and oversight flaws. These latent threats often remain hidden threats until they are uncovered through the analysis of aggregate data, such as incident reports. Conventional tools and methods, like spread sheets and database queries on their own are insufficient when searching for these lethal trends, thus more sophisticated methods and tools are required. Data mining reveals patterns that can be described as a set of incidents with common characteristics (Kirwan, 2011). In aviation, reports of accidents, incidents and other types of deviations have been collected over decades to investigate and assess risks and to set risk standards that are consistent with the preference functions of society for managing risk and safety (Janic, 2000; Sage and White, 1980). After the potential risks have been identified and quantified, corrective actions can be implemented in a timely way to eliminate the risk or to reduce it to an acceptable level (GAIN Working Group B, 2004).

Safety reports exist in the aviation industry as a result of collecting information from the large databases of multiple sources. However, enormous challenges have appeared when analysing this information (Megaputer Intelligence, 2004), yet they must be analysed as incidents eventually lead to accidents, if their progress is not prevented. To get deep into the analysis of lethal factors and to identify latent dangers, the primary factors leading to mishaps need to be identified (Dambier and Hinkelbein, 2006).

Text mining tools are already in use among the airline industry although not very widely. One of the reasons for that might be that the analytical tools used by the airlines are quite complicated and contain several capabilities, which may make them difficult to operate. However, several examples of applying data mining successfully in aviation can be found. One example is provided by JetBlue Airways, who used text mining on safety report information to deliver a more comprehensive picture of the overall safety issues in their organisation. They found patterns and possibly lethal trends in operations not previously known to be at risk (Péladeau and Stovall, 2005). Another example comes from Southwest Airlines, who used data mining tools and found particular value through the automatic extraction of important patterns, the ability to process large amounts of data, and the displaying of results in a clear and easily understandable form as well as through the ability to identify the strategic hidden knowledge and patterns in the safety data (Ananyan and Goodfellow, 2004). A third example is given by International Air Transport Association (IATA). They used classification with PolyAnalyst text and data mining in a proof-of-concept project. De-classified traffic collision avoidance system (TCAS) data from the safety trend evaluation, analysis and data exchange system (STEADES) (IATA related global aviation safety database) database were processed, leading to at least 77% of reports being correctly classified after the refinement of the original model (Goodfellow, 2004).

As airlines are business units, the volumes of events concerning safety in their daily operations are trade secrets and therefore not public and the same is true of the results of the data mining of safety data and their influence on the daily operations and management processes. However, the open test results in aviation presented here – as well as the general information about successful data mining operations – illustrate the applicability of data mining tools in the promotion of safety within the airline industry. The use of the tools is continuously being developed and Muir (2004) has stated the goal is an automated risk analysis system and the measurement of safety performance.

Quality improvement has a long history in industries and the quality management field has much to offer to healthcare and vice versa. Learning has taken place effectively when healthcare has used aviation safety techniques, such as checklists, structured communication techniques, preoperative briefings, debriefings, timeouts, error reporting and simulator training. For example, when eight hospitals around the world implemented a surgical safety checklist, the complications and deaths associated with surgery reduced significantly. The checklists in the study were designed to improve team communication and the consistency of care (Haynes et al., 2009). Also, Sax et al. (2009) found promising results by using aviation techniques in the healthcare domain. They concluded that aviation-based training increased the self-reporting of unsafe conditions and near misses and changed behaviours in the acceptance of checklists (Sax et al., 2009).

The methods in error and incident reporting and analysis in healthcare vary widely even though they all share the same purpose – to help make healthcare safer. Most of these systems have been established on the local level, which means that most of them are different and, unlike in aviation, it is not possible to compare the data between organisations (Giles et al., 2006). Reporting may be voluntary or mandatory or a combination of these. The most widely used approach is to seek and detect latent errors that have led to adverse events by analysing incident reports. In addition, reports from medical malpractice claims, morbidity and mortality and autopsies are also analysed. These methods have been important in improving patient safety, for example, in areas like anaesthesiology and pharmacy (Thomas and Petersen, 2003). A recent idea in the field is to include the patient in the reporting process. This is called patient-assisted incident reporting. Adding the patient's perspective to the reporting process is said to increase a researcher's understanding of the error or adverse event and to increase the engagement of patients in their own care (Millman et al., 2011).

Patient safety can be improved in a variety of areas. Quality can be improved through patient safety tools and measures, management and leadership, teamwork, healthcare processes and standardised and effective collection and use of the safety data (Boaden, 2006). One of the leading institutes in the development of quality improvement is currently the Institute for Healthcare Improvement (IHI) based in Cambridge, Massachusetts and founded in 1991. This institution has established one of the most utilised tools for adverse event identification in healthcare worldwide, the Global Trigger Tool (GTT). This instrument is used to identify adverse events and threats to patient safety and it is used to measure the overall level of harm in a healthcare organisation. It is an effective instrument for patient safety and quality of care improvement and is already used in hundreds of hospitals in many countries. The main purpose behind using the tool is to improve the quality of care by monitoring adverse event rates (IHI, 2012).

Recent literature on the issue criticises incident reporting systems in healthcare. It is estimated that incident reporting systems do not capture most adverse events and that up to 86% of such events may go unreported (Levinson, 2012). Barriers to incident reporting have been reported in the literature and the reasons vary from not knowing that the report system exists to under-recognition and organisational factors. One major reason why such events are not reported is a lack of trust in the anonymity and confidentiality of the reporting, which leads to a fear of blame and subsequent consequences (Pfeiffer et al., 2010). New ways to explore healthcare safety are needed to capture potential hazardous events before they occur, thus preventing them. Reason's Swiss cheese model could be used to analyse the development and outcome of lethal trends in healthcare and to improve the quality of care. The idea is to identify inconsistency in the occurrence of routine procedures by clustering the data so that precautionary actions could be taken. The question we raise for further research is: can patient document data clustering be useful as a tool for the prevention and prediction of hazardous chains of events in healthcare?

3 Methods

The flight safety data used in this research consisted of the narratives of flight safety reports for the years 1994–1996 (written in Finnish) as provided by the Finnish Civil Aviation Authority (FCAA). The data were extracted from a safety database containing approximately 16,000 safety reports. The dataset consisted of the narrative parts of a total of 1,240 safety reports on hazardous events. The size of the narratives varied from a few words (only one single word in three separate reports), to a couple of sentences. A three-year period containing more than 1,000 reports was considered, creating a 'critical mass' for producing relevant and reliable data mining results. The material used was more than 10 years old. This guaranteed that the data was already statute-barred and there were no open cases (Sjöblom and Suomi, 2009).

An essential difference between the aviation and the healthcare datasets was that the aviation records consisted of safety reports whilst the healthcare dataset consisted of all documentation concerning patient care during hospitalisation. The patient record dataset originally consisted of all electronic health records of about 26,000 patients that had been admitted to one university hospital with any type of heart problem from the year 2005 to 2009. Resuscitation that had been identified as an adverse event in the GTT, was chosen as the focus of exploration for the healthcare dataset. From the 26,000 electronic health records, we extracted all mentions of resuscitation that were contained in the narrative parts of the discharge summaries of the physicians, resulting in 1,083 text units. The size of the text units varied from a few sentences to a paragraph. Like the events described in the flight safety reports, the subject is a hazardous event that could have been prevented. Resuscitation can also lead to either a successful or an unsuccessful (lethal) outcome.

Each mention of resuscitation was represented as a bag-of-words vector (Vesanen, 2003), which encodes the context of a mention as determined by the surrounding words. In this study, ten words both before and after an occurrence were selected as the context. Each dimension of a vector indicates a weight given to a particular token (word) distinct from all other tokens. To equate words in different forms but with the same meaning, tokens were normalised. This decreases the dimensionality of the data and removes noise that may degrade the clustering performance. In order to analyse different word forms that refer to the same words, inflected word forms (e.g., patient*s,* do*es,* sle*pt*) were normalised to their lemmas (*patient, do, sleep*) using the morphological analyser FinTWOL (Koskenniemi, 1983) and the disambiguator FinCG (Karlsson, 1990) developed by Lingsoft Inc. (http://www.lingsoft.fi). The dimensionality of the data was further reduced by removing words containing non-alphabetic characters – because they are likely too diverse, e.g., all numbers are considered distinct words, or non-informative, e.g., punctuation, to contribute in the clustering step – and by converting all words into their lower case forms. The frequency vectors were transformed into a tf-idf space (Manning eta l., 2008) and the cosine similarities were calculated with Gensim (Řehůřek and Sojka, 2010). A hierarchical clustering was generated using the complete linkage method (Jain et al., 1999). Flat clusters were then obtained by applying the inconsistency criterion of 1, i.e., if the inconsistency value of a node and its descendants is at most 1, the leaf nodes belong to the same cluster. The clustering was performed with SciPy (Jones et al., 2001). Lastly, duplicate items (determined by patient id and word vector) within each cluster were removed because it was observed that, for some patients, text had been copy-pasted from one entry to another. The documents were clustered using word-space models (Sahlgren, 2006). The basic assumption in this approach is that co-occurring words define the meaning of a word or the topic of a document. Documents with similar word distributions are considered to be related to each other in these models. However, although the documents in a cluster may share a word or a topic, they may still not be meaningfully related to a human being. Thus the clusters were manually analysed by domain experts to find the topics of interest.

In the flight safety data, three systems for text mining were tested for benchmarking. One of these was totally language independent, the other had a specific configuration for Finnish and the third was originally created for English, but encouraging results have been achieved with Spanish. That was the reason for the Finnish test. Clustering was used as the method in all of the systems. The different systems processed the data and displayed the results coherently (Sjöblom, 2010). In order to get a deeper analysis from the information, the results were analysed using the quantitative data analysis application NVivo. As data mining does not give straight answers to questions, the results were examined by the main author of this article based on the skills he had gained when working at the Investigation and Analysis Unit of the Finnish Civil Aviation Authority as a flight safety inspector.

The healthcare data were analysed manually and all clusters with more than five clauses were analysed by two healthcare professionals. A topic was derived inductively for each cluster, e.g., ventricular fibrillation. Clusters that were not accumulated by the chosen subject, with clauses connected to the resuscitation or care of resuscitation, were considered irrelevant. Also, all but one clause in a cluster needed to relate to the chosen cluster topic. All relevant clusters were then examined more closely for their content. These were divided into two groups: resuscitations that presumably occurred during hospitalisation and resuscitations that occurred before hospitalisation and, from those two groups, resuscitations that occurred during hospitalisation, were chosen for examination in minute detail.

4 Results

In order to study the causes and consequences of the potentially hazardous events and the possible lethal trends, both datasets were clustered into groups of reports. This method enabled the finding of similarities between those cases that might contain some indications of a lethal trend, without having any presumption about whether such a trend existed or not.

Similar examinations were made for flight safety data using clustering as method. No preliminary definitions or limitations were made; the applied systems clustered the cases according to their basic determinations. Although the results of all the three systems were coherent, one of them can be said to have produced the most accurate results clustering 1,240 flight safety reports into 100 clusters, their sizes varied between 58 and 1 report.

The healthcare dataset included 31 clusters with more than five clauses. The cluster sizes varied from 6 to 15 clauses. These clusters occasionally included more than one clause concerning the same patient, with a variation from three to ten patients in a cluster. From the total number of 31 clusters, 28 were considered relevant and three irrelevant to the chosen subject. There were 19 clusters that indicated resuscitation during hospitalisation and nine clusters concerning resuscitation before hospitalisation. Clusters encompassing resuscitation during hospitalisation were of interest.

In the aviation data, about 20 clusters could preliminarily be regarded as containing potentially lethal trends, e.g., a door opening during a flight. Others, like flying into Finnish airspace without air traffic control clearance and illegal smoking on board during the flight as well as gliding-related events can be mentioned. During the second data mining round, refining the definitions after the first one caused a fairly small but remarkable increase in the accuracy of the results. Narratives with a single word were excluded correctly from the clustering as an anomaly by the system. Despite their disparity, the contents of the clusters seemed to be very relevant and were used as material for a more accurate examination by human investigation to find out the existence of the potential hazard in similar recurring events.

There were 19 clusters in the healthcare data with topics concerning resuscitations that presumably occurred during hospitalisation. These were: sudden cardiac arrest at the hospital, sudden vital organ dysfunction, the return of spontaneous circulation, change in condition during patient transfer, the assessment of the treatment period, laboratory values, ventricular fibrillation, acute infarction, sudden lifelessness, poor prognosis after resuscitation, successful resuscitation, the successful resuscitation of patient with diabetes and unsuccessful resuscitation. There was more than one cluster with topics concerning laboratory values, unsuccessful resuscitations and resuscitations in the hospital. The remaining nine clusters concerned resuscitation that had occurred before hospitalisation, such as background information or reason for hospitalisation.

5 Discussion

As successful data mining is an iterative process, several mining rounds are required in order to achieve accurate results. With the aviation data, two rounds were performed with two systems and one with the third one. Additional mining rounds with refined data definitions could have increased the accuracy of the results, but because the operative mining processes were executed by operators, there was no possibility for further resources at that moment. Additionally, with these rounds the expected principal results were sufficiently achieved.

The results of the flight safety reports confirmed the applicability of data mining for this kind of material, which consists of short reports written in Finnish. The applicability of the clustering method was also proved from the point of view of the key elements of aviation safety, the first of which is the importance of setting a clear goal. This means that after the mining process has revealed the existence of a possible hazard, resources to correct the situation should be allocated to ensure the prevention of that hazard. Another finding is that the analyses of the collected data should be done in a manner that allows every person involved to understand what is being sought and which changes are needed in order to develop safety. This is due to the fact that the safety of an organisation depends on everyone involved in it, not only on some people having safety in their job description.

Resuscitation was explored in the patient care documentation, a phenomenon that is identified as an incident in the GTT. Even though not all resuscitations are preventable, there are still those that might be and they need to be detected earlier and prevented. In the future, this data mining method could be tested with other concepts, such as an accident, error or incident in the large sets of patient data documentation. This would enable the exploration of other possible incidents in patient care through documentation. The further exploration of chains of events can help to develop methods that prevent incidents from happening.

Clustering patient care documentation for a chosen phenomenon, such as resuscitation, seems to be a method that can distinguish similarities in large amounts of documented patient care for further research. In the healthcare dataset, this method enabled the distinguishing of the resuscitations that presumably occurred during hospitalisation and the resuscitations that occurred before hospitalisation. Clusters concerning resuscitation during hospitalisation were of interest because they provided an opportunity to find documentation on resuscitation during hospitalisation for further exploration, such as pre-existing chains of events. The potential benefits of improving safety in healthcare are indisputable. Hazards may not be seen as an acceptable cost when healthcare is provided. This means that there is still work to be done in improving patient safety and the development of methods in order to prevent these hazards should be continuously updated.

The patient care dataset clauses consisted of ten words before and after the word ‘resuscitation’ in the patient care documentation. Due to the limitation of ten words, it was impossible to discern the chains of events that pre-existed the resuscitation in the clauses, therefore, patient care documentation, from which the clusters are constructed, needs to be examined more closely. In the future, a larger word limit could be used to discern the possible pre-existing chains of the events. From the total of 31 clusters, 19 indicated resuscitation during hospitalisation. There were also a few clusters with the same topic, which could be merged together for further analysis. If any chains of events pre-existing resuscitation were to be found in the healthcare dataset, action could be taken to develop the means to prevent such events, for example, decision support systems that alert health professionals to patients showing symptoms of cardiac arrest and patients at risk of cardiac arrest. The clauses were manually analysed by two different healthcare professionals, who understood the content of the clusters and could ensure the reliability of the healthcare dataset analysis.

The identification of hazardous events in healthcare documents may be possible in a similar way to how they are identified in aviation reports. Using clustering as method, promising results in the identification of those events have been discovered among both of the contexts, the main focus of which is the discovering and identifying of weak signals in the documentation. A total of 1,240 flight safety reports created a good sample for data mining in this context. Also the healthcare dataset was large enough to provide a comprehensive amount of data for clustering. Even though several interesting clauses were found, these clauses still need to be examined more closely in order to distinguish whether or not they could have been prevented.

Data mining does not give straight answers to the questions, but its role is purely a decision support system, although that often provides, indispensable supplementary information for the decision making processes. Thus, the representation of the discovered patterns and the assessing of their value requires that they be consolidated with existing domain knowledge because their value or significance cannot be captured using mining tools. This is why the process requires human participants with vast experience of the subject.

From the point of view of developing this study further, in addition to the narratives used in this study, other data fields might be taken into consideration in the data mining process – in order to gain more accurate results by increasing the coverage of the process. In the safety augmentation process, data mining can only be considered a speculative method in the search for lethal trends. In cases where the researchers and safety personnel know what they are looking for, business intelligence (BI) methods could be applicable as they allow the databases to be queried using numerous keywords to search for known cases of a certain type or their combinations. BI could also be applied as a complementary method when data mining is used to find something worth examining. This data can act as a query basis for BI tools that could pick up more accurate information on the type of cases found. Applying BI tools in the second phase of the process, in addition to examining the mining results more carefully, may discover additional hazardous factors in the data, guiding the safety specialist to those patterns that show where a potential accident could occur.

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