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Automatic Analysis of Critical Incident Reports: Requirements and Use Cases

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Abstract. Increasingly, critical incident reports are used as a means to increase patient safety and quality of care. The entire potential of these sources of experiential knowledge remains often unconsidered since retrieval and analysis is difficult and time-consuming, and the reporting systems often do not provide support for these tasks. The objective of this paper is to identify potential use cases for automatic methods that analyse critical incident reports. In more detail, we will describe how faceted search could offer an intuitive retrieval of critical incident reports and how text mining could support in analysing relations among events. To realise an automated analysis, natural language processing needs to be applied. Therefore, we analyse the language of critical incident reports and derive requirements towards automatic processing methods. We learned that there is a huge potential for an automatic analysis of incident reports, but there are still challenges to be solved.

Keywords. Data mining, Critical incidents reporting, Natural language processing

1. Introduction

Incident reporting systems have been a key tool to improve safety and enhance organizational learning from incidents in a range of high-risk organizations (commercial aviation, rail industry, and others). Their objective of the system is to enable users, e.g. health care professionals working for a hospital, to report in an anonymous manner critical events that occurred in their working environment. Incident reporting has been instituted in healthcare systems in many countries for some time now, e.g. in Switzerland in 1997 [1], but not in all healthcare systems it is obligatory to report critical incidents in healthcare. It has been shown that those anecdotal reports bear important information on limitations of systems and processes. For example, incident reports provide information on measures that helped in avoiding serious harm. From the quality management perspective, it is interesting to learn about the things that worked well in an incidental situation.

An analysis of the reports is difficult and currently done manually. For this purpose, incidents are collected and analysed to work out countermeasures. Often through manual analysis the total of each incident class is determined, occurrence factors and time periods are studied to identify the causes of accidents. Given the anonymous nature of the free textual messages, it is difficult to analyse roots and causes of incidents. So far, the information on critical incidents is collected, but only few hospitals are analysing the data and draw conclusions with respect to quality measures and adaptions of processes or structures. However, we can learn from frequent occurrences of messages on similar problems and from unusual constellations. At local level, i.e. within a hospital the reports

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can uncover problems or limitations in structure or workflows of a hospital. In a regional context, general problems could be determined where guidelines could help to address the challenges. Analysing beyond institutional borders is realised by external organizations such as the Stiftung Patientensicherheit (foundation for patient safety) in Switzerland or the German Medical Association in Germany.

As described, the current analysis of the reports is done manually by the quality management department in hospitals or physicians working in organizations for patient safety that run regional critical incident databases. This is clearly necessary, when going into depth and analysing origins of critical incidents. However, studying correlations and dependencies or getting a quantitative overview on frequently occurring incidents requires considering many reports at once.

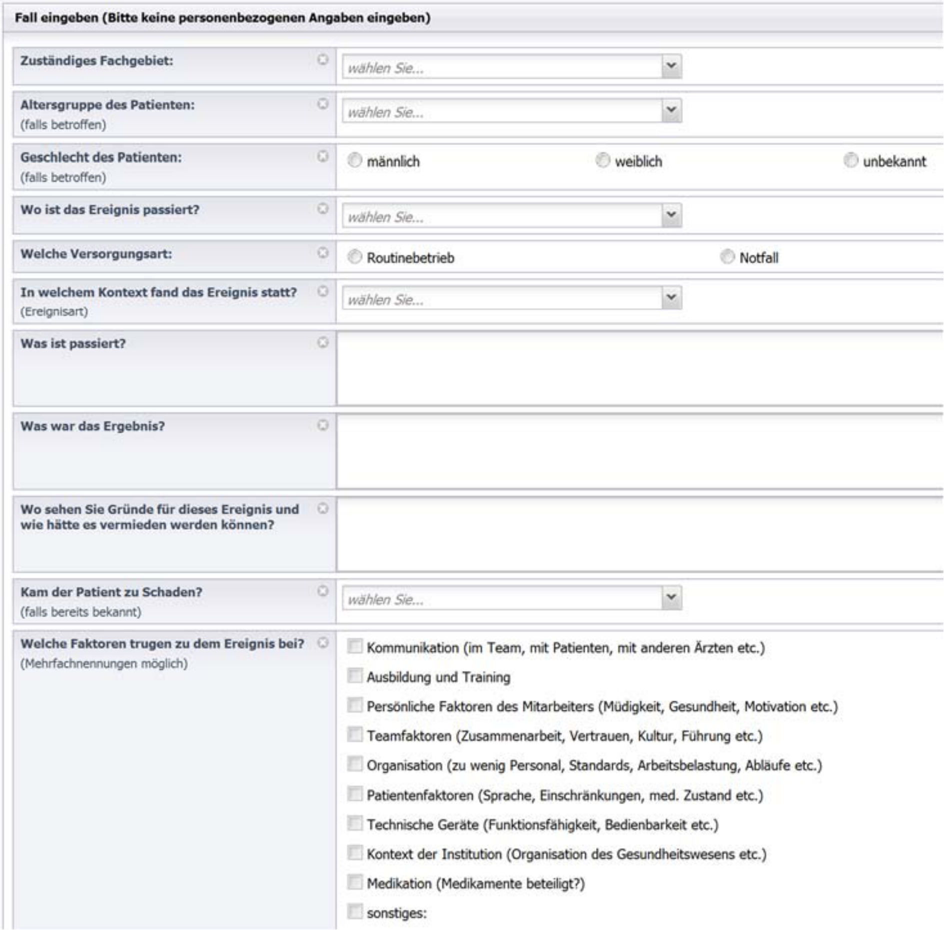
Given the unstructured nature of critical incident reports, we hypothesize that natural language processing (NLP) methods could support in analysing and processing critical incident reports. NLP of clinical narratives has sparked increasing attentions in recent years, resulting in effective algorithms for named entity recognition and relation extraction methods [2]. NLP techniques are required to make content of unstructured text machine-processable. They typically involve tokenization and sentence splitting, stop-list filtering, stemming, lemmatization, part of speech tagging, chunking and shallow or deep parsing and named entity recognition [3]. Named-entity recognition (NER) aims at identifying within a collection of text all of the instances of a name for a specific type of thing [3] (e.g., mentions of diseases or symptoms, but also persons and locations). For these basic tasks open source software is available, for example NLP tools provided by the Stanford language processing group (http://nlp.stanford.edu/software/). Domain-specific named entity recognition is enabled through tools such as MetaMap (provided by the National Library of Medicine, http://metamap.nlm.nih.gov/ [4]) or CTakes [5]. These tools map natural language text to concepts of an underlying ontology such as the UMLS. Both tools were successfully implemented and tested on clinical documents and biomedical literature. Due to the flexibility in language usage, the same meaning can be expressed in different ways, e.g. through a noun, its synonym, an abbreviation etc. Through mapping of terms to concepts of a terminology, texts can be represented semantically and become interpretable for computer algorithms.

However, it is still unclear whether these methods are already able to process incident reports or which other requirements need to be addressed. In order to develop methods for such analysis, we need to learn more about the linguistic and semantic characteristics of these reports. In this paper, we collect characteristics by means of a manual analysis of critical incident reports written in German. Further, we describe two use cases derived from discussions with physicians showing the potentials of an automatic analysis. Besides this, the main contribution of the paper is to provide a vision for an automatic analysis of critical incident reports for the purpose of using the content for quality management.

2. Material and Methods

2.1. Material

With an increasing demand for the prevention of medical accidents, critical incidents are collected in online platforms. One of those platforms is CIRS medical (http://www.cirsmedical.de) which is a reporting and learning system of the German



Fall eingeben (Bitte keine personenbezogenen Angaben eingeben)

Zuständiges Fachgebiet:	wählen Sie...
Altersgruppe des Patienten: (falls betroffen)	wählen Sie...
Geschlecht des Patienten: (falls betroffen)	männlich / weiblich / unbekannt
Wo ist das Ereignis passiert?	wählen Sie...
Welche Versorgungsart:	Routinebetrieb / Notfall
In welchem Kontext fand das Ereignis statt? (Ereignisart)	wählen Sie...
Was ist passiert?	
Was war das Ergebnis?	
Wo sehen Sie Gründe für dieses Ereignis und wie hätte es vermieden werden können?	
Kam der Patient zu Schaden? (falls bereits bekannt)	wählen Sie...
Welche Faktoren trugen zu dem Ereignis bei? (Mehrfachnennungen möglich)	Kommunikation (im Team, mit Patienten, mit anderen Ärzten etc.) Ausbildung und Training Persönliche Faktoren des Mitarbeiters (Müdigkeit, Gesundheit, Motivation etc.) Teamfaktoren (Zusammenarbeit, Vertrauen, Kultur, Führung etc.) Organisation (zu wenig Personal, Standards, Arbeitsbelastung, Abläufe etc.) Patientenfaktoren (Sprache, Einschränkungen, med. Zustand etc.) Technische Geräte (Funktionsfähigkeit, Bedienbarkeit etc.) Kontext der Institution (Organisation des Gesundheitswesens etc.) Medikation (Medikamente beteiligt?) sonstiges:

Figure 1: Entry Form of CIRS medical (*http://www.cirsmedical.de*)

association of physicians (Bundesärztekammer). The platform is accessible for everyone via Internet. Staff working in the healthcare domain can report all events associated with patient security and patient safety including errors, almost-damages, critical incidents or undesired events. A form (see Figure 1) allows to report the critical incident in a semi-structured way. Some fields are queried by multiple choices; others require free textual entries. The reports may not contain any data that allow to draw conclusions on the involved persons or institutions.

For our analysis, we collected reports from the CIRS medical website. At the time of data collection, the database contained 4703 reports (08.01.2016). For a detailed analysis, we randomly selected 100 reports from that database. No other filter criteria where applied.

2.2. Methods

The author of this paper performed a manual analysis of language peculiarities and content of the text in the free text field “What happened”, “What was good” and “What was not good". These text fields were analysed considering the questions: 1) Which characteristics and peculiarities with respect to syntax can be determined in the reports? and 2) How can the reports be described semantically? Are there certain semantic categories into which the reports can be categorised?

From our previous work on information extraction from clinical texts [6], we are aware of the peculiarities of clinical documents. Thus, we identified differences and similarities between both text types. Further, we interviewed two physicians, both responsible for analysing critical incident reports. One of them is working for the Stiftung Patientensicherheit in Switzerland, responsible for analysing the incoming reports and for selecting relevant ones for providing recommendations for the future. The other person is responsible for the incident reporting at the Inselspital Bern. We collected their experiences with critical incident reporting systems, asked for the processes and the need for analysis support. The observations from the linguistic and semantic analysis were discussed with the physicians and the results extended by their experiences.

3. Results

In this section, we summarise the results of the analysis of critical incident reports and describe the collected use cases.

3.1. Linguistic Characteristics

From the sentence structure, it can be recognised, that there is a broad spectrum ranging from short phrases to complex sentences or enumerations of phrases. Information is summarised in a few words, resulting in compound words. As already known from other clinical texts, abbreviations are used for locations (e.g. "iv" for "intravenous") or for procedures or technical devices (e.g. "ECMO" which is a kind of life support machine). Clinical texts are known to be error prone since they are written under time pressure [6]. In contrast, the analysed incident reports did not contain many writing errors. Since often processes are described, temporal and other number expressions are exploited. Table 1 summarises the characteristics and provides examples from the reports. Differences to

Table 1. Linguistic Characteristics of Critical Incident Reports

Characteristic	Example
Broad spectrum in sentence complexity: Complex sentences, short phrases	„Der Kreislauf verschlechterte sich rapide, es konnte der Katecholaminschenkel schnell auf eine peripher venöse Kanüle gewechselt werden, welche zufälligerweise noch nicht, wie geplant, entfernt worden war.“
	„Ungenügende Fixierung des ZVK“ (insufficient fixation of central venous catheter)
Abbreviations	ECLS/vaECMO
Number expressions	Zugriffszeit ca. 2 min. (access time 2 min)
	nach ca. 15 Sekunden (after 15 seconds)
	SpO2 von 100% (SpO2 of 100%)
Subjective vs. Factual information	Die größte Gefahr der Verletzung besteht beim…(The largest danger of injury occurs during…)
Compound words	Zustandsverschlechterung (State worsening)

Table 2. Categories of Critical Incidents with Examples

Category	**Example**
Technical events or events related to equipment	*Oxygenator is burning*
Administrative events	mistaken identity, ambiguous abbreviation as diagnosis, language barrier, mixing of laboratory probes
Hygiene-related events	Report on a case of Methicillin-resistant Staphylococcus aureus (MRSA) / hospital infection
Workflow-related issues	application of wrong drug, allergy information was not transmitted to all involved persons
Events related to transport and positioning of patient	Patient is falling from operating table

clinical documents are mainly related to the semantics and content described. They are summarised in the next section.

3.2. Semantic Characteristics

Semantically, the texts are rich of information. While specific terms referring to diagnoses are seldom explicitly mentioned, the texts contain descriptions of symptoms, procedures (e.g. *Intubationsnarkose (intubation anesthesia), nachbeatmet (ventilated), Ambulanz-OP (ambulant surgery)),* or names of pharmaceutical agents, narcotics etc. In contrast to clinical documents such as discharge summaries, various material, either technical or non-technical are mentioned including *monitor, emergency rucksack, blood pressure cuff* etc. Additionally, the locations of events occurrences are described such as *laboratory, emergency department, anaesthetic recovery room, intensive care unit* and others.

Different persons involved in the event are presented in the reports by their role. Besides the patient, e.g. *staff working on the various wards, ward physician, anaesthetist, emergency doctor, person responsible for blood transfusion, child, nurse, director* and others are mentioned in the reports. All these pieces of information together result in detailed descriptions of critical incident events in their timely order. Sometimes, it is only mentioned what happened without any further explanation. There are also non-medical events described (such as mistaken identity of patients) that resulted in clinical events. More specifically, we can distinguish five categories of events. They are listed with examples in Table 2.

In particular in the section asking for good or bad things, we can find subjective information and factual information or even speculations. Consider the sentence „Es hätte zu einer Entzündung, Thrombophlebitis und einer Fibronisierung des Fremdkörpers kommen können“ (An inflammation, thrombophlebitis and fibronisation of the foreign body could have occurred). It is not yet confirmed that these issues happened to the patient, but the author of the report is mentioning them already.

3.3. Automatic Analysis of Critical Incident Reports: Use Cases

Through interviews with physicians, we identified several use cases where an automatic analysis of incident reports is required: 1) Retrieval of and access to reports and 2) automatic assessment and analysis of incident reports. They are described in more detail in the following.

3.3.1. Faceted Search for Retrieval of Critical Incident Reports

Situation: A physician wants to know, whether a problem that he recognised happened before and which countermeasures had been taken.

Problem: The database of critical incident reports is difficult to query. If at all, only predefined categories allow to filter the reports. A free textual or even semantic search for similar cases is not yet implemented. The free text fields are not searchable.

Use Cases: There are two possible use cases. On the one hand, an improved retrieval of relevant reports is necessary. One option would be that for a given critical incident report relevant cases are to be retrieved. The query would be the report and the result would comprise a set of similar reports.

On the other hand, the entire database of reports could be actively searched, e.g. for reports of a certain category. Consider an incident that occurred, and a quality manager or physician who would like to know which measures had been taken when the event occurred before. A structured and semantically enriched critical incident data base could provide answers by returning all relevant cases with retrieval results structured by the taken measure.

Technical Solution: To enable these use cases, in particular the content of the free text fields needs to be semantically analysed and mapped to concepts of an ontology. This would result in a normalised representation of the text. This representation could form the basis for enabling a faceted search [7]. Faceted search, or faceted navigation is a technique that allows to assess information using a faceted classification system. The technique enables users to explore a collection of information by applying multiple filters. Each information element is assigned to multiple explicit dimensions, called facets. For the first use case, the retrieved records would be made browsable by their facets. In the second use case, the retrieved reports would be accessible by the measure taken.

3.3.2. Critical Incident Analytics

Situation: The quality management of a hospital is interested in learning about frequently occurring critical incidents and wants to analyse correlations for developing in-house guidelines or improved processes. They want to learn about limitations in process or structure quality. Further, they would like to know how often which type of incident occurs.

Problem: The web-based systems for reporting critical incidents not yet provide methods for an automatic assessment and aggregation of data. A challenge is the unstructured text in the reports.

Use Case: For a given problem or event statistics have to be created, how often the event occurred etc. An automatic analysis could determine event-cause chains that allow to get insights into processes causing the critical events.

Technical Solution: Using text and data mining methods, and semantic technologies the incident reports could be automatically analysed, semantically enriched with categories. Relations such as those between an event and its cause could be determined and prepared for user assessment. The texts could be automatically assigned to semantic categories and text could be normalised by indexing (assigning concepts of an ontology to normalise the content). The categorization could be realised according to type of reported problem (e.g. hygiene, complication during treatment), location (e.g. intensive care unit, laboratory), or severity. Methods for detecting events, causes and measures in unstructured text are required for this purpose.

4. Discussion and Conclusions

Critical incident reports are still an unused resource of knowledge on quality issues in the health care sector in general or in a hospital in particular. While it is recognised that the reports could support in identifying risks and limitations, there is no technical support available to analyse the content systematically or in retrieving relevant information. Currently, the reports are manually analysed which results in an almost non-use of the data. A semantic analysis of the data could enable multiple use cases. Yamamoto et al. performed a linguistic analysis for incident reports in English. They extracted characteristic words using natural language processing and they evaluated the degree of similarities between incident documents [8]. Lee et al. [9] used data mining to identify critical factors in patient falls using a web based reporting system. Using artificial neural network analysis they developed a predictive model and identified several critical factors. However, to the best of our knowledge there is no system available that supports the use cases described in this work.

As a first step towards developing technologies that enable the introduced use cases, in this paper, we collected the linguistic peculiarities of critical incident reports: They make several demands on the technologies which partially differ from those of clinical documents. In contrast to natural language processing methods developed specifically to process clinical documents, methods for analysing critical incident reports require:

- Methods for identifying persons and locations,
- Methods for separating factual from experiential or hypothetical information,
- Methods for categorizing incident reports semantically and of events according to severity,
- Methods for detecting events and their relations,
- Methods for analysing time and number expressions.

Additionally, methods for semantic structuring and analysis are necessary. As a next step, we will study which existing tools and methods can be used to support these tasks. For identifying persons and locations named entity recognition tools such as those provided by the Stanford NLP group could be used. Some first research has been done to separate factual from experiential or hypothetical information from clinical documents [10] and for extracting time information (e.g. Heideltime [11]).

Further, the use of ontologies and formal concepts of a domain is necessary for adapting inference functionalities to various situations and application scenarios, but also to make unstructured text automatically processable within the context of reasoning. For mapping to an ontology, we need to study, whether incident reports could be indexed of classified using the International Classification of Patient Safety (ICPS), a classification system for incident cases [12]. This classification system could form the basis for a faceted search and semantic annotation of the reports. Methods for an automatic mapping to this classification system are still missing. First attempts regarding automatic classification of incident reports using machine learning algorithms have been made by Ong et al. [13]. But, they used only two categories and not the ICPS. In summary, as next steps, methods for realising the text analysis tasks mentioned before need to be developed or existing methods adapted. An incident report analysis tool need to combine multiple methods for natural language processing.

Our analysis was done in a qualitative manner. The results could be confirmed by a quantitative assessment of the reports with respect to word classes and frequent occurring patterns. However, for collecting requirements towards the development of NLP methods, our analysis provide already comprehensive results. We used the data from CIRS medical for our analysis. It might be that these messages are selected manually by the hosts of the system to show only representative reports. This might be an explanation why we could not identify writing errors as expected.

Given the results from our study in this paper, we recognize potentials and use cases for text and data mining of critical incident reports. An improved access to experiential knowledge has the potential to improve patient safety, and quality of care which in turn are benefits that would help in increasing physician's motivation of reporting such events.

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