Triangulating Safety: Applying Social Media Analysis Methods to Revolutionize Patient Safety

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contrast, has been poorly utilized, creating a vicious cycle, where such underutilization leads to lower reporting rates, leading to even lower utilization. It is obvious that free text description can paint a much more accurate picture of how an event occurred, including the information on interaction among multiple health care workers involved in the events, and temporal sequence of events. The more seasoned a safety manager of a hospital is, the more emphasis she would place on ‘qualitative’ data. Then, why are these data being underutilized? The lack of resources is probably an answer: Some of such data are composed of just a couple of sentences, but there are many reports with longer descriptions. The Johns Hopkins Hospital, using the Patient Safety Net run by University Health System Consortium (UHC), allows health care workers to type up to 1,000 letters in an event description. No RLS, past or present, have the huge human resources to read all the reports and extract information from them. Therefore, safety researchers have usually compromised. We read only the free texts from the events that caused serious harm, in other words, unfortunately, many had to ignore the free texts description from less severe events. Though a seemingly logical compromise, it might be a dangerous choice. First, as mentioned above, less serious events or near misses have the same occurrence mechanism as serious events. Therefore, there is no reason to leave them unanalyzed; they are a huge missed opportunity to prevent future errors. In addition, health care workers are frustrated by their elaborate reports being ignored, and become less likely to report errors.

Triangulating Safety: Hints from Social Media Analysis

What if we can analyze the apparently disorganized free text description of an event as much as the quantitative part with predefined variables of the RLS data? What if we can extract key factors of an incident and complex network of constituents of the event from the text? Combining this data with the structured data, we are obviously in a better position to see where and how the event occurred, leading us to predict future events in hospitals. This ‘corroboration’ of two major parts of error reports, in that they can locate the vulnerable sites, processes and picture detailed mechanism how events occurred, we call the ‘triangulation of safety.’ Indeed such mixing of quantitative and qualitative methods is called triangulation [7].

Let us elaborate by using an illustrative example of submitted report about patient fall case. The quantitative part collected the following information, such as, type: patient fall, time: 11PM, location: corridor near a ward, harm: hip joint fracture. These gave us much information on the event, but let us take a look at the free text description that was filled out by a nurse: “A patient who was supposed to be discharged in two days fell while he went to bathroom and broke his left hip joint in a corridor on a ward at 11PM. Though no caregiver was around the patient, he did not call the nurse because he did not want to bother her. 9PM, two hours before the incident, a resident physician gave an order to a nurse to give the patient Lasix (diuretics). It was only to adjust fluid output to the fluid intake of the day. The nurse raised a concern in giving Lasix in the late night, but was ignored. The attending physician was very bossy to his trainees. For the resident, in and out of water was more important than the risk of patient fall.” This free text description gave us a completely different picture of the event.

In this incident, the hip fracture was the ultimate harm to the patient, as captured in the multiple-choice section of the report. However, the section was unable to capture the causal chain of events, including the attending physician’s bossiness, the power gradient among different Health care worker types and administration of Lasix at night, insufficient caregiver attention and patient’s reluctance to summon the nurse. A thorough examination of the free text description of the event can provide much richer information, although the quantitative part still helps us to conduct efficient exploratory analysis on a huge amount of RLS data. There is no doubt that triangulation would be much better in preventing errors.

There have been attempts to analyze the free text data from error reports [8,9], but they were all done manually by human coders. Considering the huge amount of the free text data, automated analysis by computer or at least computer-assisted analysis is essential. Then, a couple of questions naturally arise: whether we have algorithms to analyze those free text data on medical errors, and if so, whether we have enough computing power to process such a huge flow of free text data. The answers would have been no and no only a few years ago, when most RLS were developed and started operation. But now, the answers might be yes and yes. Information Technology has evolved as fast as medical care has.

We can get some hints from social media. Every day 4.75 billion pieces of content items on Facebook and 500 million tweets are posted on Twitter [10,11], and they still manage to extract information to administer tailored advertisements and suggest new content that individual users might like. A professional social-networking site, LinkedIn, analyzes all the texts (though more categorized than Twitter or Facebook) you post as well as your relationships with other users, to suggest the best people to connect with or the most fitting job offers. Indeed, computing power can certainly satisfy the level to which all medical error reports collected with RLS can be analyzed in almost real-time, yielding information that had not been noted when an incident was reported.

In addition, automated content analysis enables researchers to extract emotional status of a person or his or her feeling about the conversation or description [12]. The accuracy of automated analysis results was shown to match that of human-coded results [13,14]. This can even be used to understand various cultural issues that were known to affect safety, such as teamwork climate, stress recognition, and job satisfaction of health care workers [15]. The above-mentioned methods, despite their sure benefits, are yet to be applied to error reports data.

Conclusion

In sum, we can completely change the way of using RLS. Up to now, RLS has given us bird’s eye view of how many and what kind of errors and harmful events occur in the field of health care. Now we need a truffle-hunter’s view of each event to understand exactly what happened, who and how people were involved and in what context. Only then will we be able to effect a dramatic improvement in safety.

Now, with all these new tools and techniques at our disposal, and more importantly with the huge medical error data
“Do we have the right not to do this work, the work that can save millions of lives?”

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Conflict of Interest

None.

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