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Integrating Human Patterns of Qualitative Coding with Machine Learning: A Pilot Study Involving Technology-Induced Error Incident Reports

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Abstract. The objective of this research was to develop a reproducible method of integrating human patterns of qualitative coding with machine learning. The application of qualitative codes from the technology-induced error and safety literatures to the analysis of incident reports was done successfully, helping to identify the factors that lead to an error as well as the errors themselves. The method described in this paper may provide additional insights into understanding technology-induced errors.

Keywords. Patient safety, health technology, health technology safety, technology-induced error

1. Introduction

Health technologies such as electronic health records (EHRs) are fundamental to providing healthcare [1, 2]. Although some technologies convey health benefits to patients and/or improve healthcare processes, other technologies may influence safety (i.e. technologies may introduce new types of errors). Internationally, healthcare organizations are attempting to identify methods that can be used to obtain an in-depth understanding of safety events using automated analytic approaches [1]. In this research we developed a reproducible approach to integrating human patterns of qualitative coding with machine learning (ML). The method will be tested for its feasibility in qualitatively coding text based technology-induced error incident reports submitted by health professionals and citizens, who have observed or experienced such events. The method builds on prior research focused on quality improvement, technology safety and learning health systems [3-6].

2. Objectives

The objectives of this research were to: (1) explore the feasibility of integrating qualitative coding with ML based on human patterns of coding technology-induced

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errors and (2) identifying the issues and considerations arising from the application of the coding scheme and ML methodology to text based technology-induced error reports.

3. Literature Review

Research has documented how technologies can decrease medical error as well as how they can introduce new types of errors (i.e. technology-induced errors). Technology-induced errors arise from the: "a) design and development of a technology, b) its implementation and customization, c) interactions between the operation of a technology and the new work processes that arise from a technology's use" [3, p. 388], d) its maintenance, and e) the interfacing of two or more technologies used in the process of patient care [3,4]. Qualitative and quantitative methods have been used to study technology-induced errors. Qualitative methods afford researchers' the ability to describe the error, while quantitative methods (i.e. machine learning and cluster analysis) help to identify potential technology-induced errors in text based incident reports typically found in incident reporting databases [5,6]. There have been a few studies that have been published that have employed human coding of incident reports [5] and others that have applied machine learning approach to coding incident reporting data.

4. Method

In this section of the paper we will describe the method that will be used to test the feasibility of the human coding of text based incidence reports, followed by machine learning that uses human identified patterns for analyzing technology-induced errors found in text based incident reports. We initially downloaded two years of safety incident data (i.e. 2019-2020) from the MAUDE FDA database. The MAUDE FDA database contains error reports about medical devices. The top six electronic health record (EHR) vendors, which represent over 91% of market share were identified in the data. The manufacturer's names were then used to extract the incident reports involving EHRs and their subsystems (e.g. ePrescribing) [7]. This allowed us to identify a subset of reports. The remaining reports were then reviewed by two researchers by applying the definition for technology-induced error [3, 4]. An incident report was included for qualitative coding, if the definition of a technology-induced error applied [3,4]. If the report did not fit the definition, it was excluded from the qualitative analysis. Each of the incident reports were reviewed in this manner. Each researcher read through the report independently and then indicated whether the report should be included or excluded. In cases, where the two researchers agreed, the report was retained for further analysis. In cases where the researchers disagreed on whether the report should be excluded or retained, the researchers reviewed the report together and discussed it until all the differences in their reviews were resolved. This was done until a final set of incident reports was identified for further analysis (See Figure 1). The final set of incident reports were then uploaded to NVivo12 Plus®. Following this, a directed content analysis approach was used to code the incident reports. The approach employed qualitative codes from the published technology-induced error and health technology safety literature. The unit of qualitative analysis took the form of words, phrases, sentences, and paragraphs. Each unit of analysis was the smallest unit of understandable information. The granularity of qualitative codes was determined by technology-induced error concepts (and their corresponding definitions from the literature on technology-induced errors) [8]. Two researchers coded each unit of analysis and disagreements were resolved with discussion. Approximately 60% of the incident reports were coded manually (as described in the steps above) and this manual coding was used to train the NVivo software to automatically detect human-identified patterns using ML (using its AutoCoding capability). The remaining incident reports were then automatically analyzed for type of error and outcome [9].

5. Results

2,900,950 records were downloaded from the MAUDE FDA database for the 2019 to 2020 period. The number of incident reports were then further reduced to 269 incident reports when the names of the top EHR vendors that represent 95% of US market were extracted from the downloaded data. These incident reports were then reviewed by two health informatics experts with human factors expertise. Incident reports were further excluded if they did not fit the definition of a technology-induced error as described in [3,4]. 30 incidents reports remained (see Figure 1). After the initial human coding was completed for the first half of the reports, this was followed by the automated coding of the remaining reports. Two experts then reviewed the coded segments from the automated portions and it was found there was complete agreement between the human coders. Then, NVivo12 was used to automate the detection of human identified patterns based on the human coded segments.

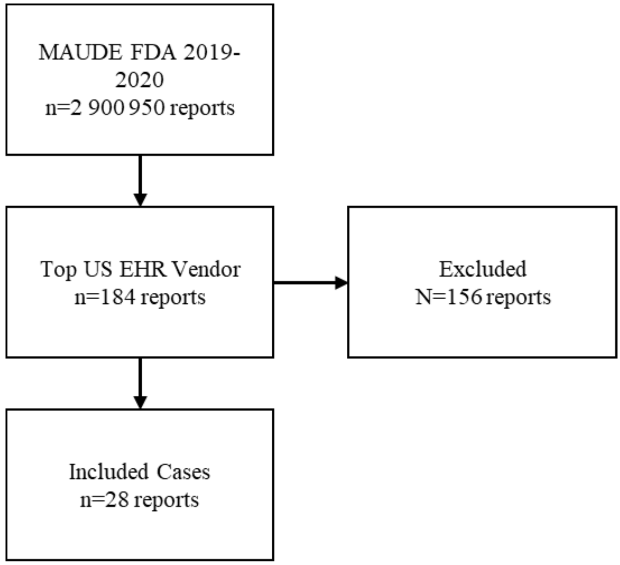

Figure 1. Incident Technology-induced Error Incident Reports

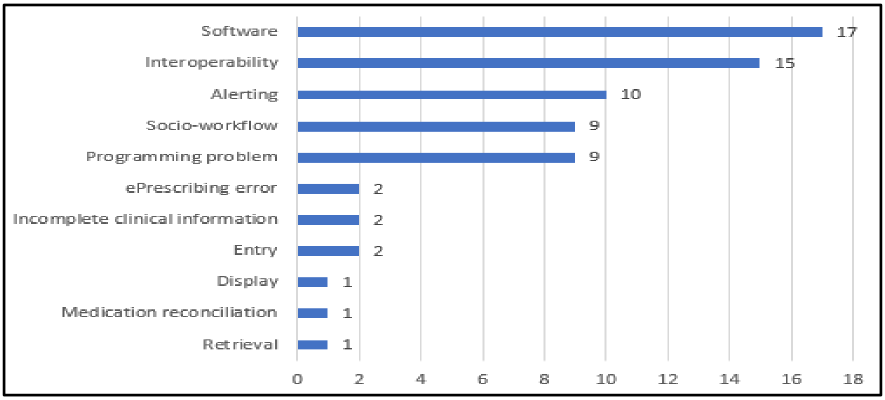

Figure 2. Frequency Distribution of Input Factors that Contributed to Technology-induced Errors

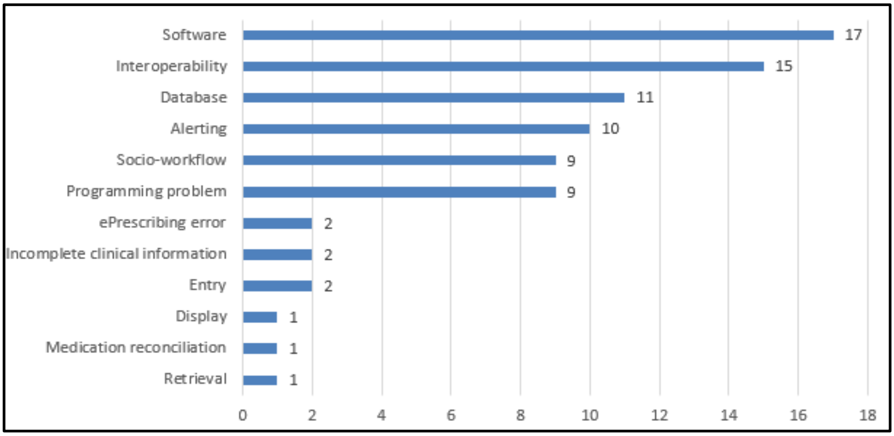

Figure 3. Frequency Distribution of Technology-induced Error Outputs

In Figure 2 the approach was able to detect that codes for software, interoperability, alerting, database and workflow problems were the most frequently reported. From Figure 3 it can be seen that issues such as wrong dose, missing medications, wrong drug and delay in care were also the most frequently reported output issues.

6. Discussion

The use of ML based on human patterns of coding is a feasible method for coding text based incident reports describing technology-induced errors. This represents a hybrid human-machine approach to analyzing large databases of reports and articles. The approach holds considerable promise in speeding up the process of coding for differing types of technology-induced errors. The manual portion of coding took several days but this was speeded up with the automated portion being coded in close to real time. Our initial codes were from the error literature involving technology. Machine learning based on human patterns were used to train the ML algorithm (using the NVivo AutoCoding capability). We are currently experimenting with determining how much of the coding needs to be done manually (i.e. by a human coder) to find out what is the least amount of manual coding needed as input to the automated coding process while still retaining the accuracy of the coding as compared to human coders. As technologies change over time, there is a need to periodically develop new codes for new and emergent errors and then train the algorithm to identify new technology-induced errors documented in the incident reports. The hybrid mixed methods approach described in this paper holds considerable promise for making the analysis of ever increasing data sets with error reports more efficient and feasible.

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