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A Keyword Approach to Identify Adverse Events Within Narrative Documents From 4 Italian Institutions

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Objectives: Existing methods for measuring adverse events in hospitals intercept a restricted number of events. Text mining refers to a range of techniques to extract data from narrative sources. The goal of this study was to evaluate the performance of an automated approach for extracting adverse event keywords from within electronic health records.

Methods: The study involved 4 medical centers in the Region of Lombardy. A starting set of keywords was trained in an iterative process to develop queries for 7 adverse events, including those used by the Agency for Healthcare Research and Quality as patient safety indicators. We calculated positive predictive values of the 7 queries and performed an error analysis to detect reasons for false-positive cases of pulmonary embolism, deep vein thrombosis, and urinary tract infection.

Results: Overall, 397,233 records were collected (34,805 discharge summaries, 292,593 emergency department notes, and 69,835 operation reports). Positive predictive values were higher for postoperative wound dehiscence (83.83%) and urinary tract infection (73.07%), whereas they were lower for deep vein thrombosis (5.37%), pulmonary embolism (13.63%), and postoperative sepsis (12.28%). The most common reasons for false positives were reporting of past events (42.25%), negations (22.80%), and conditions suspected by physicians but not confirmed by a diagnostic test (11.25%).

Conclusions: The results of our study demonstrated the feasibility of using an automated approach to detect multiple adverse events in several data sources. More sophisticated techniques, such as natural language processing, should be tested to evaluate the feasibility of using text mining as a routine method for monitoring adverse events in hospitals.

Key Words: adverse event, keywords, electronic health record

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Adverse events (AEs) are unintended harm caused by medical management rather than by the patient's underlying condition.[1] Adverse events affect between 2.9% and 16.6% of all hospitalized patients and 30% and 58% of all AEs are preventable.[2] Of preventable AEs, 20% to 25% result in permanent disability or death and account for between U.S.$17 and U.S.$29 billion in additional health care costs annually.[1,2]

Accurate, timely and efficient methods for monitoring AE rates are required to evaluate the success of preventive measures. Existing systems for measuring AEs in hospitals have some limitations.[3] Discharge diagnostic codes have low sensitivity and positive predictive values (PPVs).[4] In addition, they suffer from coding errors and lack of temporal information, and are typically available several months after discharge, thus limiting timely surveillance of AEs and prompt interventions.[5,6] Manual chart review is a time-consuming, resource-intensive, and costly process.[4] Incident reports underestimate the true incidence of AEs,[7] and a significant lag time between AEs and submission of reports limits early detection of AEs.[8]

With the advent of electronic health records, a rich source of valuable clinical information is becoming available. However, most of the information in patients' records consists of unstructured narratives, such as discharge summaries,[9,10] emergency department notes,[11–13] and operation reports.[14,15]

Text mining refers to a range of techniques to extract data from narrative sources.[16,17] The keyword approach is an automated method that screens narrative documents for relevant words ("trigger words") that are used to represent AE concepts within free-text notes. Prior studies demonstrated the suitability of keyword approaches for identifying adverse drug reactions,[18] postoperative complications,[19] medical concepts,[20] or diseases,[21] and screening for mentions of the risk of falls.[22]

Our working group previously conducted a pilot study to validate the accuracy of using a text mining tool for detecting cases of hospital-acquired pneumonia. We selected 23,745 discharge summaries and 19,126 narrative radiology reports for patients admitted to the Niguarda Ca' Granda Hospital (Milan) in 2007. We developed a lexicon to categorize pneumonia-related terms, then we performed a clustering analysis matching our predefined list of terms with words in narrative documents. We validated the classification output in a sample of 2071 documents automatically extracting information from emergency department notes or pneumonia-specific records, or against manual chart review if automated sources were not available. The tool performed well in terms of sensitivity (91.8%), specificity (97.4%); positive and negative predictive values were 63.6% and 99.6%, respectively.

Few studies have tested text mining on samples of documents across multiple institutions.[23–25] In this study, we developed a keyword approach to identify AEs within narrative documents from 4 Italian institutions. The goal of this study was to describe the development and test the performance of the tool against a criterion standard (domain expert chart review). We have tried to present the strengths and limitations of the approach, taking into account future directions of text mining in this area of research.

METHODS

In 2015, the Italian National Agency for Regional Health Services started a project to improve patients' safety and quality of care. The development of a system integrating available data sources for measuring AEs at regional and national levels was a specific goal. On this basis, risk managers from 4 Italian medical centers evaluated and selected candidate data sources and AEs. A research protocol was developed to establish the methodology and outcome measures.

The study was conducted in 2017 and involved 4 medical centers in the Region of Lombardy: Ca' Granda Ospedale Maggiore Policlinico Foundation, ASST Pavia Trust, ASST Papa Giovanni XXIII of Bergamo Trust, and ASST Fatebenefratelli Sacco of Milano Trust.

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AQ4 The authors disclose no conflict of interest.

T1 Table 1 presents some quantitative data regarding the 4 centers, such as number of beds, number of admissions (ordinary/day hospital, surgical, and emergency department admissions), surgical procedures, and low-complexity care interventions/low-intensity operations. Overall, in 2016, the 4 centers made 144,840 ordinary/diurnal admissions, which represented more than 11% of all ordinary/diurnal admissions in Lombardy in that year.

The study population included

- all patients with discharge dates between January 1 and December 31, 2015, and
- all patients who accessed emergency departments between January 1 and December 31, 2015.

Electronic health records were collected and processed anonymously. Data sources included discharge summaries, emergency department notes, and operation reports. Data sources not available in electronic form were excluded from the analysis.

Seven AEs were selected, including those used by the Agency for Healthcare Research and Quality as patient safety indicators (PSIs):

- postoperative wound dehiscence
- perioperative pulmonary embolism
- perioperative deep vein thrombosis
- urinary tract infection
- return to the operating room
- foreign body left in during procedure
- postoperative sepsis

Adverse events were targeted because of their impact on a patient's disability, duration of stay in hospital, death, and health care costs.

In this study, we used a computer application known as the AQ5 3M360 Encompass System. This tool provides an interface for conducting searches across records using keywords. These words could be used by physicians to represent AE concepts within records. The 3M360 Encompass System allows for combinations of multiple keywords in queries, including both words to highlight and words to exclude. Wildcard characters are also supported by the application.

Our study included several phases.

First, a starting set of keywords for each AE was developed. Words were selected based on risk managers' clinical knowledge and experience, and on a literature review.

The first set of words was applied to the entire sample of records. Any record that contained a keyword was considered "positive." A convenience 5% sample of positive records were reviewed by the entire team to detect true and false positives. False positives were reviewed to assess causes of misclassification and, consequently, to modify the initial group of keywords. The computer application was also trained to include significant words (positive terms), exclude other words (negative terms), and use wildcard characters (e.g., the character * allowed for inclusion of terms derived from a root form).

Words were combined with Boolean operators (and, or, not) to make more specific combinations of words. This process was repeated several times, until the teamwork did not identify any false positives in the 5% sample of positive records.

On this basis, a final query for each AE was developed. These queries were applied to the entire sample of records not previously analyzed (Fig. 1). Each member of the team selected a single AE F1 and manually reviewed positive records to detect true and false positives. After the individual review, the entire team revised all records to obtain agreement.

Two AEs ("foreign body left in during procedure" and "return to the operating room") were searched for within a single data source (operation reports), whereas the full set of records was screened to detect the other 5 AEs.

We assessed the validity of the tool by calculating the PPV as the rate of positive records with an AE according to the manual chart review divided by the total number of positive records. Sensitivity was calculated for one AE ("foreign body left in during procedure") through manual review of a 5% convenience sample of negative operation reports.

In addition to calculating PPVs, a quantitative error analysis was performed to detect reasons for false positives. The analysis focused on 3 AEs: perioperative pulmonary embolism, perioperative deep vein thrombosis, and urinary tract infection.

RESULTS

The data sources were 34,805 discharge summaries, 292,593 emergency department notes, and 69,835 operation reports. Overall, 397,233 records were collected (Table 2). T2

Table 3 shows the number of positive records for each AE T3 across the different data sources. "Urinary tract infection" was the AE in 90.38% of the positive discharge summaries and 89.04% of the positive emergency department notes; however, the performance of keywords was tested on a 10% convenience subsample of positive documents (n = 286). As expected, 66.54% and 21.97% of positive operation reports included words about "return to the operating room" and "foreign body left in during procedure," respectively.

Table 4 shows the number of positive terms, negative terms, T4 and wildcard characters within each query. Overall, we used 85

TABLE 1. Quantitative Data Regarding the 4 Medical Centers

Hospital	Beds, n	Admissions, n			Surgical Procedures, n	Low-Complexity Care Interventions/Low-Intensity Surgery, n
		Ordinary/Diurnal	Surgical DRG	ED		
1	1690	57,051	20,800	237,324	30,124	7149
2	1005	42,731	17,644	104,196	23,475	2363
3	938	31,051	10,295	144,258	10,086	3372
4	168	14,007	4496	32,271	5192	99

1, ASST Papa Giovanni XXIII; 2, IRCCS Ca' Granda Foundation Ospedale Maggiore Policlinico; 3, ASST di Pavia; 4, ASST Fatebenefratelli Sacco (Buzzi Hospital).

ED, emergency department.

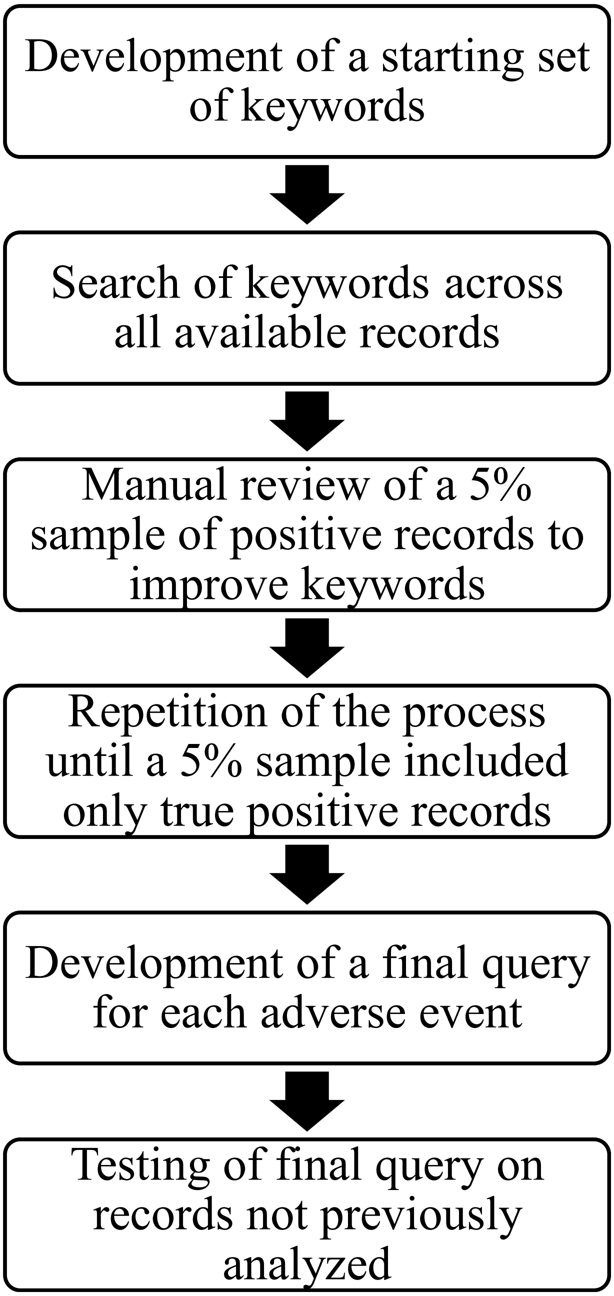

FIGURE 1. Overview of the method.

positive terms, 57 negative terms, and 43 wildcard characters. The final query about "foreign body left in during procedure" was extremely structured because the team included several terms to represent retained items or device fragments such as "sponge," "needle," "swab," "gauze," and excluded nonrelated words such as "coin," "calculus," "tooth," "splinter," "insect," and many others. Thirty-two wildcard characters were introduced to capture heterogeneous terms using their root form. Similarly, the final query about "return to the operating room" included terms indicating both complications (such as "bleeding," "perforation," and "laceration") and unplanned procedures.

T5 Table 5 shows the results of our validation study. The PPVs were highest for "postoperative wound dehiscence" (83.83%) and "urinary tract infection" (73.07%) and lowest for "perioperative deep vein thrombosis" (5.37%), "postoperative sepsis" (12.28%), and "perioperative pulmonary embolism" (13.63%). It should be noted that, although the word "catheter" or its radical forms were not included in the search query for "urinary tract infection," during manual chart review, only records in which the urinary tract infection can be attributed to the positioning of a catheter during hospitalization were considered true positives, even in cases where the invasive maneuver was not explicitly reported by the physician in the text.

Sensitivity was 100% for "foreign body left in during procedure."

Table 6 shows the results of quantitative error analysis. The 3 T6 most common reasons for false positives were reporting of past events, negation, and conditions suspected by a physician but not confirmed by a diagnostic test. Overall, 42.25% of false positives were mentions of past events, such as "history of" or "previous." Among false-positive cases of urinary tract infection, 68.83% were past events. In addition, 22.80% of false-positive records included negation (such as "no signs of"), whereas 11.25% included suspected AEs, not identified through imaging studies from diagnostic radiology (e.g., venous ultrasound, computed tomography scan of the chest) or through laboratory tests (e.g., urine culture).

TABLE 2. Data Sources From the 4 Medical Centers

	Data Source, n		
Hospital	**DS**	**EDN**	**OR**
ASST Papa Giovanni XXIII	NA	91,269	34,258
IRCCS Ca' Granda Foundation Ospedale Maggiore Policlinico	NA	90,960	24,460
ASST di Pavia	20,480	110,364	11,117
ASST Fatebenefratelli Sacco (Buzzi Hospital)	14,325	NA	NA
Total	34,805	292,593	69,835

DS, discharge summaries; EDN, emergency department notes; NA, not available; OR, operation reports.

TABLE 3. Positive Data Sources for Each AE

	Positive Data Source					
	DS		OR		EDN	
AE	**n**	**%**	**n**	**%**	**n**	**%**
Postoperative wound dehiscence	4	0.51	79	10.09	16	0.66
Perioperative pulmonary embolism	21	2.69	0	0.00	67	2.76
Perioperative deep vein thrombosis	27	3.46	8	1.02	151	6.22
Urinary tract infection	705	90.38	1	0.13	2.160	89.04
Return to the operating room	0	0.00	521	66.54	0	0.00
Foreign body left in during procedure	0	0.00	172	21.97	0	0.00
Postoperative sepsis	23	2.95	2	0.26	32	1.32
Total positive record	780	100.00	783	100.00	2.426	100.00

DS, discharge summaries; EDN, emergency department notes; OR, operation reports.

TABLE 4. Characteristics of Each AE's Final Query

AE	Final Query		
	Positive Terms, n	Negative Terms, n	Wildcard Characters, n
Postoperative wound dehiscence	6	0	2
Perioperative pulmonary embolism	11	3	0
Perioperative deep vein thrombosis	8	2	1
Urinary tract infection	9	3	2
Return to the operating room	18	1	5
Foreign body left in during procedure	24	45	32
Postoperative sepsis	9	3	1

There were other reasons for false-positive cases of perioperative pulmonary embolism and deep vein thrombosis (Table 7). These included cases of non–deep venous thrombotic disease, such as arterial, superficial vein, or "other site" thrombosis; expressions for thromboprophylaxis or thrombolysis; mentions of symptoms included in our queries but not reflecting the occurrence of an AE (such as dyspnea and tachycardia); hematological diseases such as essential thrombocythemia; and misclassification of abbreviations (e.g., "ep" in the sense of "episode" rather than "pulmonary embolism").

DISCUSSION

The results of our study demonstrated the feasibility of using an automated keyword approach to detect multiple AEs in several data sources.

A key challenge for improving patients' safety is an accurate detection of the occurrence of AEs. Traditionally, hospitals rely on incident reporting systems, manual review of clinical charts, and administrative data for monitoring AEs. However, these methods provide information late and intercept a restricted number of events, so researchers have focused their attention on novel approaches to extract data from electronic health records. Prior studies extracting data from narrative sources through a keyword approach concentrated on a limited number of data sources and AEs. Like us, Hanauer et al[26] used a computer application (EMERSE) to perform standardized searches across records. They developed bundles containing words to search for, words to ignore, and wildcard characters. Several sources were screened within an integrated electronic health record system, but only 2 AEs were considered, pulmonary embolism and myocardial infarction. Sensitivity ranged from 92.8% to 100% and specificity ranged from 93.0% to 95.9% compared with the results of manual chart review. In our study, we calculated only the PPVs, but we searched for 7 AEs, some of which required development of intricated queries due to variability of expressions. Murff et al[19] developed 11 AE categories and 95 trigger words that might be used to represent AEs resulting in disability at discharge, prolonged hospitalization, transient disability, or abnormal laboratory results. Only discharge summaries were screened for AEs. Overall, the PPV of the tool was 52%. In our study, we analyzed 7 AEs, but multiple data sources were screened. Penz et al[27] analyzed physicians' progress notes, nursing notes, operation reports, discharge summaries, and administrative data to identify central venous catheter (CVC)–related AEs. They used a phrase-matching algorithm to search large

TABLE 6. Reasons for False-Positive Cases of Pulmonary Embolism, Deep Vein Thrombosis, and Urinary Tract Infection

False Positive	AE			
	PE	DVT	UTI	Total
Past event				
n	32	54	53	139
% Col.	42.11	30.68	68.83	42.25
% Row	23.02	38.85	38.13	100.00
Negation				
n	11	56	8	75
% Col.	14.47	31.82	10.39	22.80
% Row	14.67	74.67	10.67	100.00
Suspected				
n	12	9	16	37
% Col.	15.79	5.11	20.78	11.25
% Row	32.43	24.32	43.24	100.00
Other				
n	21	57	0	78
% Col.	27.63	32.39	0.00	23.71
% Row	26.92	73.08	0.00	100.00
Total				
n	76	176	77	329
% Row	23.10	53.50	23.40	100.00

% Col., % column; DVT, deep vein thrombosis; PE, pulmonary embolism; UTI, urinary tract infection.

TABLE 5. Validation of the Automated Tool's Performance

AE	PR, n	TP, n	FP, n	PPV, %
Postoperative wound dehiscence	99	83	16	83.83
Perioperative pulmonary embolism	88	12	76	13.63
Perioperative deep vein thrombosis	186	10	176	5.37
Urinary tract infection	2866*	209*	77*	73.07
Return to the operating room	521	207	314	39.73
Foreign body left in during procedure	172	57	115	33.13
Postoperative sepsis	57	7	50	12.28

*The analysis was conducted on a 10% subsample of positive documents (n = 286).

FP, false positives; PPV, positive predictive value; PR, positive records; TP, true positives.

TABLE 7. Other Reasons for False-Positive Cases of Pulmonary Embolism and Deep Vein Thrombosis

Other Reasons for False Positives	AE	
	DVT	PE
Abbreviations, n	0	7
Mentions of symptoms, n	0	14
Non-VTE thrombosis, n	38	0
Prophylaxis/procedures, n	8	0
Hematological diseases, n	11	0
Total, n	57	21

DVT, deep vein thrombosis; PE, pulmonary embolism; VTE, venous thromboembolic disease.

pieces of text for specific word combinations and a scoring system to define patterns reflecting probable CVC-related AEs. The tool yielded a PPV of 41%. Multiple data sources were tested, but only one specific type of AE was searched for.

In our study, we achieved PPVs ranging from 5.37% to 83.83%. There were several issues related to false positives. The 3 most common reasons were reporting of past events, negation, and conditions suspected by physician but not confirmed by a diagnostic test. Past events were not excluded because the application screened the entire record rather than specific sections. Physicians mentioned concepts related to previous hospitalizations in the "past history" section, and our searches intercepted these terms. Evidence from the literature suggests using algorithms for decomposition of records and analysis of sections of interest.[28,29] However, this strategy was not suitable for our sample of electronic health records. Although several negative terms were included within queries, negation led to false positives in many cases. In fact, although it was relatively simple to exclude some nonrelevant words (such as "coin" and "tooth"), it was challenging to exclude all expressions that physicians used to negate the presence of a symptom (such as "no fever") or the occurrence of an AE (such as "no recent episodes of urinary tract infection"). As suggested in the literature, more sophisticated negation detection algorithms are needed to improve precision.[30] Similarly, we detected several ways to report a suspected condition in records (such as "hypothesis of"), but in many cases, the condition was not confirmed by diagnostic tests, thus leading to false positives. Moreover, we tracked the abbreviations that physicians used most frequently to describe an AE, and we included them into queries during the iterative process (e.g., "tep" for pulmonary embolism or "tvp" for deep vein thrombosis). This allowed us to reduce but not eliminate false positives (7 false positives for pulmonary embolism were due to misclassification of abbreviations). We did not search for a sample of misspelled words during the iterative process that physicians have accidentally inserted into the text of a record, which cannot be recognized by the software. Despite this problem, in our study, the sensitivity for an AE (foreign body left in during procedure) was 100%. It should be noted that in our study we used an "exact keyword matching" approach, which does not take into account synonyms, and a "case-insensitive matching" approach, which detects keywords in uppercase or lowercase letters.

Our study has some strengths. We analyzed a large sample of 397,233 records including a collection of heterogeneous types of document from different medical centers. The queries were developed in an iterative process to mimic a common way that physicians document an AE. It should be noted that we searched for AEs posing a substantial challenge because of variability in definitions and terminologies used to describe them. However, our approach performed quite well. Several researchers have described methods for extracting information from reports using text mining techniques, but in some cases, the research setting was ideal because of automated data readily available and high quality of record keeping in large hospital networks.[18] In our study, we simply shared documents and demonstrated the generalizability of the method across 4 different sites. Moreover, this automated approach allows for real-time surveillance of AEs, which could be monitored prospectively, whereas discharge diagnostic codes to calculate PSIs are available only after discharge. Evidence in the literature suggests that text mining techniques have significantly greater sensitivity compared with PSIs, with only a small reduction in specificity.[31] However, although we selected 5 AEs from Agency for Healthcare Research and Quality PSIs, we did not compare the performance of our tool with PSIs that used discharge coding information in 2015.

Our study has some limitations. First, we evaluated the validity of the keyword strategy using only PPVs. Because of the low prevalence of the selected AEs, manual review of a large sample size of documents was required to detect true and false negatives, so sensitivity was calculated only for retained surgical items (foreign body left in during procedure). We calculated the PPV, which is affected by prevalence. To express the ability of a test to detect a complication, a positive likelihood ratio should be reported, thus requiring calculation of sensitivity and specificity. Second, automated methods to identify AEs require the availability of electronic health records. Although the adoption of electronic health records is improving, some medical centers currently use paper-based clinical documents,[32] and the introduction of automated methods of AE detection is not feasible. Third, perhaps the greatest limitation, is that the keyword strategy is a highly customized approach and does not cover a broad range of medical concepts and reporting practices and styles. Researchers have started to develop novel and potentially more accurate methods of AE detection, such as natural language processing, which uses computer-based linguistics and machine-learning approaches to extract information from free-text data. Natural language processing tools incorporate medical vocabularies such as the Unified Medical Language System for knowledge representation, considering hierarchical relations among extracted concepts, acronyms, abbreviations, and idiosyncratic language.[33–35] Predefined algorithms allow for the exclusion of past events from the analysis and concentration on specific sections of a record, such as the "hospital course" section of discharge summaries, to ensure detection of events occurring during the index hospitalization.[36] Using natural language approaches, FitzHenry et al[37] achieved PPVs of 23% for pulmonary embolism and 44% for postoperative sepsis, whereas Penz et al[27] obtained a PPV of 70.5% for CVC-related AEs.

In future research, we will develop rule-based algorithms and use natural language processing approaches to detect AEs within electronic health records from multiple medical centers. We hypothesize that this method will successfully identify more AEs than do traditional monitoring systems and keyword strategies.

CONCLUSIONS

Our study suggests the potential of automated approaches to detect AEs from within electronic health records, even using a simple strategy such as keyword queries. More sophisticated techniques such as natural language processing should be tested to evaluate the feasibility of using text mining as a routine method for monitoring AEs in hospitals.

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