Towards Prevention of Acute Syndromes

Electronic Identification of At-Risk Patients During Hospital Admission

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Summary

Background: Identifying patients at risk for acute respiratory distress syndrome (ARDS) before their admission to intensive care is crucial to prevention and treatment. The objective of this study is to determine the performance of an automated algorithm for identifying selected ARDS predisposing conditions at the time of hospital admission.

Methods: This secondary analysis of a prospective cohort study included 3,005 patients admitted to hospital between January 1 and December 31, 2010. The automated algorithm for five ARDS predisposing conditions (sepsis, pneumonia, aspiration, acute pancreatitis, and shock) was developed through a series of queries applied to institutional electronic medical record databases. The automated algorithm was derived and refined in a derivation cohort of 1,562 patients and subsequently validated in an independent cohort of 1,443 patients. The sensitivity, specificity, and positive and negative predictive values of an automated algorithm to identify ARDS risk factors were compared with another two independent data extraction strategies, including manual data extraction and ICD-9 code search. The reference standard was defined as the agreement between the ICD-9 code, automated and manual data extraction.

Results: Compared to the reference standard, the automated algorithm had higher sensitivity than manual data extraction for identifying a case of sepsis (95% vs. 56%), aspiration (63% vs. 42%), acute pancreatitis (100% vs. 70%), pneumonia (93% vs. 62%) and shock (77% vs. 41%) with similar specificity except for sepsis and pneumonia (90% vs. 98% for sepsis and 95% vs. 99% for pneumonia). The PPV for identifying these five acute conditions using the automated algorithm ranged from 65% for pneumonia to 91 % for acute pancreatitis, whereas the NPV for the automated algorithm ranged from 99% to 100%.

Conclusion: A rule-based electronic data extraction can reliably and accurately identify patients at risk of ARDS at the time of hospital admission.

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Background

Since the landmark report from the Institute of Medicine more than a decade ago [1], health information technology has been identified as a potential solution to health care safety and its potential to improve patient care has been emphasized [2]. The rapidly increasing adoption of electronic medical records (EMR) provides an unprecedented opportunity to utilize the technology as a tool for syndrome surveillance and to enhance the safety of critically ill patients through development of "smart alarms" [3-5].

Acute respiratory distress syndrome (ARDS) is a common ICU syndrome with high mortality [6]. Accurate, early identification of patients at risk of ARDS at the time of initial Emergency Department (ED) assessment provides the opportunity to initiate effective prevention strategies [7, 8]. It is also critical for successful enrollment of patients in prevention trials. The recently developed and validated Lung Injury Prediction Score model (LIPS) is a score that identifies patients at high risk of ARDS early in the course of their illness and before ICU admission [8]. This score assigns points both for conditions that predispose patients to ARDS (e.g., shock, aspiration, sepsis, pancreatitis, pneumonia, high-risk surgery) and ARDS-modifying factors (e.g., sex, alcohol abuse, obesity, chemotherapy, diabetes mellitus, smoking) at the time of hospital admission. It has been shown that the cumulative score is a reliable predictor of the risk of developing ARDS during hospitalization [9]. Most of the variables used for calculating the score and defining the risk predictor are readily available during the first 24 hours of critical care.

However, the need for timely identification of these risk factors may limit the use of this prediction score. Traditionally, researchers calculate these kinds of scores by manually extracting data from a patient's medical records [8]. This process is usually performed every day by study coordinators and the data is then reinstated into the research databases. These processes are time-consuming, inefficient, and also carry the risk of inaccuracies due to errors in manual data extraction and manual data entry [10, 11]. With the continued adoption of EMRs, the risk of using manually collected data is substantially reduced [2], and more timely identifications of at-risk patients is occurring [12, 13]. However, EMR data manipulation and secondary use have their own limitations [14, 15]. The quality of data can be suboptimal and the need to check data for accuracy and validation is essential [16].

In this study, we aimed to develop and validate automated data-extraction strategies (automated algorithms) to identify selected ARDS risk factors that are required for LIPS calculation at the time of hospital admission. Our hypothesis is that compared to the manual data extraction, automated data extraction strategies can reliably identify selected ARDS risk factors with sensitivity similar to or exceeding that achieved by manual data collection.

Methods and Study Population

The study population is a secondary analysis utilizing a subset of an ongoing prospective study for ALI/ARDS prevention [9]. Briefly, the study cohort included Olmsted County, Minnesota residents exhibiting risk factors (see below) for ARDS at the time of hospital admission. Exclusion criteria for this cohort were: age <18 years old, prisoners, pregnancy, those who refused consent to use their medical records in research and a second/consecutive admission during the same year of the study period.

Trained investigators extracted data from the electronic medical records of patients and confirmed the presence of specific ARDS risk factors according to standardized definitions. From the above-mentioned cohort, we used subset patients who were admitted to the hospital during 2010 for our analysis. The patients from the first half of the year 2010 (N = 1562) were used for the derivation cohort. The patients from the second half of the year 2010 (N = 1443) were used for the validation cohort.

Only acute conditions occurring during the first 24 hours of hospital admission were considered. We included five acute conditions (sepsis, aspiration of gastric content into the lungs, pneumonia, acute pancreatitis and shock). ►Table 1 summarizes the acute conditions studied along with the ac-

tual medical definition used by manual data extraction and the definition used for EMR electronic search (pragmatic definition), in addition to the EMR tables or note sections used.

Data Extraction Methods

Manual data extraction

Risk factors were manually ascertained within 24 hours of hospital admission by the research coordinator using the recently developed and validated Lung Injury Prediction Score model (LIPS) [8]. All variables were collected from the electronic medical records of patients with risk factors admitted through the emergency department. Every morning the research coordinator would screen the patients admitted during the previous 24 hours.

Automated electronic note search strategies

In this study, we utilized data from the Mayo Clinic Life Sciences System (MCLSS). MCLSS is an exhaustive clinical data warehouse that stores patient demographics, diagnoses, and hospital/laboratory/clinical notes and pathology data gathered from various clinical and hospital source systems within the institution. MCLSS encompasses a near real-time(NRT) model of some of the institution's EMR tables. Data Discovery and Query Builder (DDQB) was the tool used to access the data contained within the MCLSS database [17]. The DDQB is based on Boolean logic to create free text searches using a natural language processing (NLP) strategy.

In addition to DDQB, our group also utilized data from a custom integrative relational research database that contains a near real-time copy of clinical and administrative data from EMRs. The Multidisciplinary Epidemiology and Translational Research in Intensive Care (METRIC) datamart accumulates pertinent multiple source data within an average of 15 minutes from its entry into the EMR and serves as the main data repository for rules development. More detailed structures and contents have been previously published [18].

The algorithm for each acute condition was developed and continuously refined to improve the sensitivity and specificity, as outlined in ▶ Figure 1 illustrating the general structural flow of development and validation of each condition (▶ Appendix-Table 1).

For automated extraction of acute medical conditions, MCLSS/DDQB and Metric datamart were used to interrogate the EMR of each study patient within a 24-hour period of hospital admission. Clinical note search queries were restricted to the following sections of the clinical notes: Diagnosis, Impression/Report/Planning and Assessment/Planning. Data regarding vital signs, laboratory values and medication administration (SIRS criteria vital signs (respiratory rate, heart rate, temperature), laboratory values (Leukocytes), medications (antibiotics – used as a method for indicating suspicion of infection) were extracted from the Metric datamart. To optimize sensitivity, each query was designed to identify the condition of interest and the common synonyms, acronyms and abbreviations, or vital signs, laboratory values and medication administration were used to represent the condition. To improve specificity, we excluded negative terms of the condition of interest (no, not, negative, unlikely) as well as terms referring to a history of the condition (history of, recent) mentioned in the clinical notes. Following the initial building of the queries for the acute condition, query building was an iterative process in a derivation cohort. Searches were performed and the results were analyzed by reviewing all false positive and false negative cases when compared to the manually ascertained risk factors. On the basis of this analysis between the manually ascertained risk factors done by the research coordinator and the automated search strategies of these risk factors, more key terms, synonyms, acronyms, abbreviations were added and more negative terms were excluded. The algorithm was then run again and false positive and false negative cases compared again, algorithm modified again, if necessary, then tested, etc. until a satisfying sensitivity and specificity was achieved. Once finalized in the derivation cohort, no further changes to the query were made and the queries were then validated in another independent cohort where the risk factors had also been previously ascertained manually by the research coordinators.

A. Ahmed et al.: Electronic Identification of Disease Risk Factors

ICD-9 code search

The MCLSS was used to identify selected acute conditions according to the ICD-9 diagnosis code as described in ▶Appendix-Table 2.

Reference standard

The reference standard was defined as the agreement between the ICD-9 code, automated and manual data extraction. Because the diagnosis of these acute conditions was often not obvious at the time of hospital admission, two study investigators, who were masked to the data extraction result, independently reviewed medical records charted within the first 24 hours of hospital admission and adjudicated all discordant results between the three search strategies. In case there was a disagreement between two reviewers, a third independent investigator also blinded to the results would make the final adjudication.

Statistical Analysis

Baseline characteristics of derivation and validation cohorts were summarized as mean and standard deviation or median and interquartile range for continuous variables, and number and percentage for categorical variables.

As our primary analysis, sensitivity and specificity for each search strategy was calculated based on the comparisons of the search results and the reference standard in both the derivation and validation cohorts. Positive (PPV) and negative predictive values (NPV) were calculated as well. Percentage agreement and Cohen's kappa statistics comparing manual and electronic data extraction were used as our secondary analysis. JMP statistical software (version 9.0, SAS, Cary, NC) was used for data analysis.

Results

A total of 3,005 patients admitted to hospital during the year 2010 were included in the study. The derivation cohort included 1,562 patients admitted during the first six months of 2010. The validation cohort consisted of 1,443 patients admitted during the second half of 2010. The demographic characteristics and baseline comorbidities of the derivation and validation cohorts are summarized in ▶Table 2.

▶Table 3 summarizes the sensitivity and specificity of the automated algorithm, manual data extraction and ICD-9 code search for five acute conditions in the validation cohort. Compared to the manual data extraction, the automated algorithm had higher sensitivity for identifying sepsis (95% vs. 56 %), aspiration (63% vs. 42%), acute pancreatitis (100% vs. 70%), pneumonia (93% vs. 62%) and shock (77% vs. 41%) with similar specificity except for sepsis and pneumonia (90% vs. 98% for sepsis and 95% vs. 99% for pneumonia). Compared to ICD-9 code search, the automated algorithm had higher sensitivity for detecting cases of sepsis (95% vs. 51%), pneumonia (93% vs. 77%), acute pancreatitis (100% vs. 90%) and shock (77% vs. 55%) but had lower sensitivity for detecting cases of aspiration (63% vs. 84%).

The PPV for identifying these five acute conditions using an automated algorithm ranged from a minimum of 65% for pneumonia to a maximum of 91 % for acute pancreatitis, whereas the NPV for the automated algorithm ranged from 99% to 100%. ▶Table 4 summarizes the prevalence, PPV and NPV of the automated algorithm, manual data extraction and ICD-9 code search for five acute conditions in the validation cohort.

There was considerable agreement between electronic and manual data extraction (>80%), with low to high Cohen's kappa statistics (range 0.40–0.78). ▶Table 5 summarizes the agreement percentage and Cohen's kappa statistics between manual and electronic data extraction in the validation cohort.

Discussion

The study result from a single center using retrospective data suggests the level of feasibility and validity of rule-based electronic data extraction of a number of acute conditions from the EMR. Using readily available data, electronic identification of patients at risk of ARDS during their hospital stay may offer an opportunity to implement timely interventions to prevent the syndrome. Moreover, it could assist in the enrollment of participants in prevention, early treatment and intervention trials.

There is strong evidence of a benefit of early intervention for patients admitted with critical syndromes including acute coronary syndrome [19], severe sepsis and septic shock [20], and terminal cancer [21]. However, identification of these critically ill patients represents an abundant challenge. In a research setting, scientists have long sought to solve the problem of time-consuming chart review using automated methods, and this was demonstrated in the time span of studies included in a systematic review by Stanfill et al [22]. The electronic method used in this study can also be beneficial in research settings and in enrolling patients in clinical trials, particularly when enrolling minorities presents greater challenges [23]. Furthermore, many applications can benefit from early identification of acute conditions, including many platforms of decision support systems, faster screening and enrollment in clinical trials, clinical research and syndrome surveillance and for enhancing compliance with evidence-based practices.

Our results are similar to other studies which used the same concept of keyword electronic text search. For example, Hanauer et al. was able to reach a sensitivity of 1.0 and specificity of 0.93 for myocardial infarction [24]. To ascertain risk factors for post-operative pulmonary complication, Kor et al. used a similar approach to identify preoperative risk factors and used them to develop a lung injury prediction score for surgical patients [25]. Singh et al. used a similar tool to identify chronic comorbidities required to calculate Charlson scores, and his results showed the electronic algorithm was superior to the International Classification of Diseases, Ninth Revision diagnostic (ICD-9) code search [26].

In multiple studies, the use of administrative data like ICD-9/10 codes in a research setting has proven its lack of accuracy [26-28] – except for the aspiration – our results were not different. In a recent study by Bensley et al, ICD codes were unreliable and inadequately identified at-risk patients [29]. Another option is to use Systematized Nomenclature of Medicine – Clinical Terms (SNOMED-CT) codes. Studies have demonstrated the superior performance of SNOMED-CT over ICD-9/10 codes [30], but it has its own limitations such as some care elements terminology representations, particularly when scientific scales are used [31]. Moreover, some studies suggested low reliability and the need for trained providers to execute the SNOMED-CT concepts [32]. Finally, applying coding concepts will require time, and usually will not be available for screening within a few hours of patient admission.

Another method would be to add more advanced Natural Language Processing (NLP) techniques to discriminate high-value textual information. In a multicenter study, Fitzhenry et al. was able to identify – with some variability – post-operative complications using NLP [33]. However, these NLP techniques require specific software and rigorous training as well as large training datasets [34]. Additionally, data extraction using NLP may not be robustly accurate [35]. As an alternative, our approach, which incorporates calculated rules similar to actual disease definition, promises more accuracy and portability and can be used by providers and researchers without extensive expertise in NLP. For example, sepsis was identified with greater sensitivity (95% vs. 88%) in the present study vs. Fitzhenry's NLP study. In the case of sepsis condition, the use of labs and vital table's rules to calculate systemic inflammatory response syndrome (SIRS) might have significantly contributed to the superior performance of our algorithm. Nevertheless, our automated algorithm had lower PPV in sepsis and aspiration and this can be due to the lower prevalence of the two conditions in the studied sample.

Our study has a number of limitations. First, the number of events in some conditions is small which reflects either low prevalence or underdetection, but the electronic rule result had higher sensitivity compared to the manual data extraction. The low prevalence of conditions of interest also leads to a low Kappa value despite a high agreement percentage. Second, the terms and phrases used in the text search may be specific to our own institution, and can change over time due to the turn-

over of in-training physicians. Nonetheless, encouraging the use of homogeneous language and more structured notes may facilitate easier data extraction from clinical notes. Third, all data utilized in this study depended solely on EMR content, which in some instances may not represent the true world or events and may contain errors [16]. Furthermore, some of the discrepancies between the manual and the electronic algorithms might be due to the fact that some of the EMR data came late in the process after manual data abstractors already looked up the notes. However, the manual data collection was performed by trained providers and rechecked again while adjudicating discrepancies to generate the reference standard. Also, the database used to run these algorithms may not have the desired consistency, which can limit the applicability of this approach in institutions using similar or other databases. With more advances in EMRs, indexing of clinical notes will generate more stable databases and facilitate better outcomes for this approach. Finally, the single-center, academic nature of our institution could raise the concern of referral bias as well as overall generalizability.

Conclusion

Utilizing an existing EMR, an electronic rule-based search strategy was able to identify patients with risk factors for ARDS with more accuracy and higher sensitivity than manually collected data. The feasibility and ease of use of these electronic algorithms can facilitate the incorporation of such strategies into clinical decision support systems and screening processes for medical research and clinical trials.

Abbreviations and Acronyms

- **CI** = Confidence interval
- **DDQB** = Data Discovery and Query Builder
- **EMR** = Electronic medical record
- **ICD-9** = International Classification of Disease, Ninth Revision
- **ICU** = Intensive care unit
- **IQR** = Interquartile range
- **MCLSS** = Mayo Clinic Life Sciences System
- **NPV** = Negative predictive value
- **PPV** = Positive predictive value
- **SNOMED-CT** = Systematized Nomenclature of Medicine – Clinical Terms

Conflicts of interest
The authors declare that they have no conflicts of interest in this project.

Protection of human and animal subjects
The Institutional Review Board approved the study protocol and waived the need for informed consent since no direct involvement of human subject.
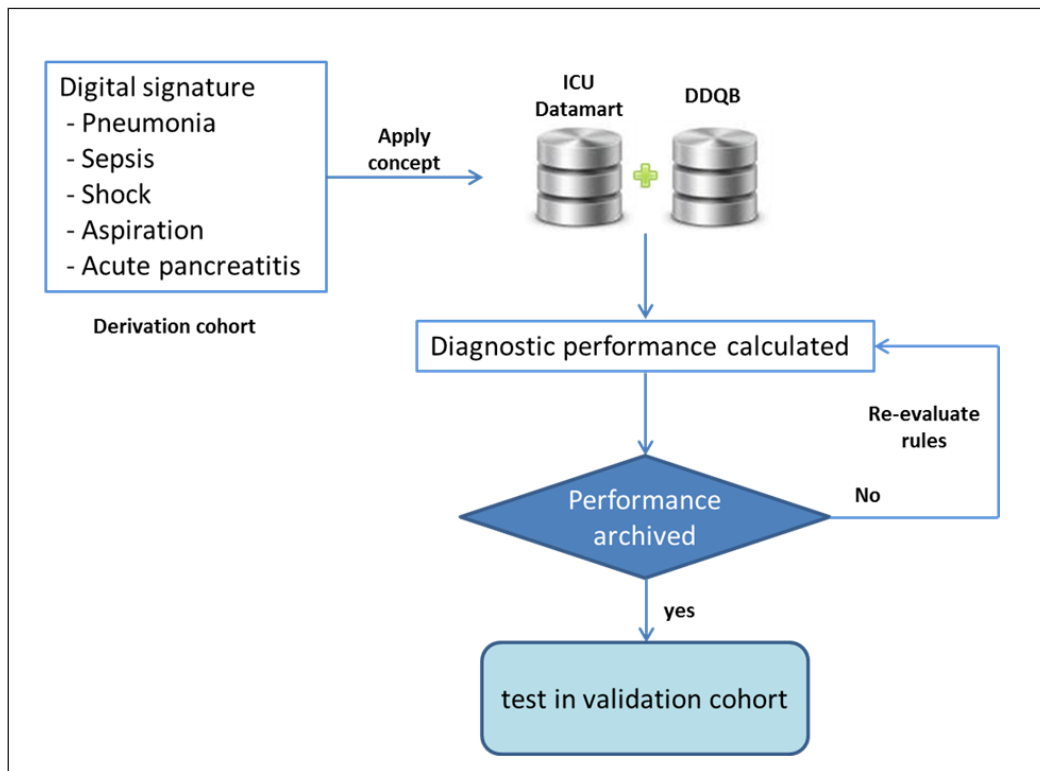
Fig. 1 Study procedure

Table 1   Definitions of included acute conditions

Condition	Medical definition (m)	EHR definition (pragmatic definition)	EHR section used (Source table)
Pneumonia: (new infiltrate + clinical suspicion)	1. New or progressive radiographic infiltrate + High clinical suspicion of pneumonia (New cough, sputum, fever or WBC>12) Or 1. NEW Abnormal chest radiograph of uncertain cause + Microbiological or serological evidence of definite or probable pneumonia + Low or moderate clinical suspicion of pneumonia	Text search for the word pneumonia	Diagnosis, impression and plan note sections.
Sepsis: (SIRS + infection)	Suspected or documented infection + More than one of the following clinical manifestations (any 2): 1. Body temperature greater than 38°C or less than 36°C 2. Heart rate greater than 90 beats per minute 3. Respiratory rate greater than 20 breaths per minute, Or hyperventilation, as indicated by a PaCO2 of < 32 mm Hg 4. White Blood Count greater than 12,000/cu mm, a count less than 4,000/cu mm, or the presence of more than 10 percent immature neutrophils ("bands")	Lab and vital search for SIRS criteria. Heart rate and respiratory rate must be present at the same hour twice to be considered. Any two conditions must be present on the same day to be considered. For suspicion of infection empiric antimicrobial order during the first 24 hours was applied.	Lab table, vital signs table, medication table and diagnosis section of the note.
Shock	Suggested by any use of vasopressor **OR** history & examination and markers of inadequate perfusion as: 1. Central venous oxygen saturation (ScvO$_2$) or, mixed venous oxygen saturation (SvO$_2$) less than 70%, 2. Blood lactate levels greater than 4 mmol/L in the absence of known acute or chronic liver disease 3. Increased base deficit < −4 4. Blood pH less than 7.32	Presence of the shock index at least twice per hour or use of pressers medications outside operation room.	Vital table, medication administration table.
Aspiration	Witnessed or suggestive history of inhalation of food or regurgitated gastric contents	Text search algorithm	Diagnosis, impression and plan note sections.
Acute Pancreatitis	Two of the following three features: 1. Abdominal pain characteristic of acute pancreatitis 2. Serum amylase and/or lipase >/ 3 times the upper limit of normal 3. Characteristic findings of acute pancreatitis on CT scan	Lab search for elevated level of serum amylase and/or lipase (Lipase > 140 U/L, Amylase 150 U/L) along with text search algorithm	Lab table, Diagnosis, impression and plan note sections. Diagnosis, impression and plan note sections.

Table 2   Baseline characteristics between derivation and validation cohorts

Characteristic*	Derivation cohort (N = 1562)	Validation cohort (N= 1443)	P value
Age M (SD)	63 (20)	63 (20)	0.49
Female, n (%)	735 (48)	666 (47)	0.65
White, n (%)	1412 (90)	1287 (89)	0.27
APACHE III score, median (IQR)	58 (42–74)	59 (40–78)	0.79
Diabetes mellitus, n (%)	438 (28)	375 (26)	0.21
Hypertension, n (%)	947 (61)	857 (59)	0.49
Chronic heart disease, n (%)	183 (12)	144 (9)	0.13
COPD, n (%)	80 (5)	49 (3)	0.02
ICU Admission, n (%)	452 (29)	404 (27)	0.55
LIPS score , median (IQR)	2 (1–3)	2 (1–2.5)	0.33
ICU mortality, n (%)+	14 (3)	15 (4)	0.61

*Data are reported as number (%) or median (25%-75% interquartile range). + For those admitted to ICU only.
APACHE = Acute Physiology and Chronic Health Evaluation; COPD = chronic obstructive pulmonary disease

Table 3   Sensitivity & specificity for automated digital algorithm, manual data extraction and ICD-9 code search in the validation cohort.

Condition	Automated digital algorithm		Manual data extraction		ICD-9 code search	
	Sensitivity (%) (95% CI)	Specificity (%) (95%CI)	Sensitivity (%) (95% CI)	Specificity (%) (95%CI)	Sensitivity (%) (95% CI)	Specificity (%) (95%CI)
Sepsis	95 (85–99)	90 (85–93)	56 (43–68)	98 (95–99)	51 (38–64)	99 (96–99)
Pneumonia	93 (86–96)	95 (94–96)	62 (53–71)	99 (98–99)	77 (68–84)	98 (97–99)
Aspiration	63 (39–83)	99 (99–99)	42 (21–66)	99 (99–99)	84 (60–96)	99 (98–99)
Acute pancreatitis	100 (80–100)	99 (99–99)	70 (46–87)	100 (99–100)	90 (69–98)	99 (99–99)
Shock	77 (62–88)	99 (99–99)	41 (27–57)	99 (99–99)	55 (39–69)	99 (99–99)

CI: confident interval

Table 4   Prevalence, PPV and NPV for automated digital algorithm, manual data extraction and ICD-9 code search in the validation cohort.

Condi-tion	Cases no.	Preva-lence (%)	Automated digital algorithm		Manual data extrac-tion		ICD-9 code search	
			PPV (95%CI)	NPV (95%CI)	PPV (95%CI)	NPV (95%CI)	PPV (95%CI)	NPV (95%CI)
Sepsis	61	19.1	69 (58–78)	99 (96–99)	87 (72–95)	90 (86–93)	91 (75–98)	89 (85–93)
Pneumonia	122	8.5	65 (58–72)	99 (99–99)	80 (70–87)	97 (95–97)	78 (69–85)	98 (97–99)
Aspiration	19	1.3	86 (56–97)	99 (99–99)	80 (44–96)	99 (99–99)	48 (31–66)	99 (99–99)
Acute pan-creatitis	20	1.4	91 (69–98)	100 (99–100)	100 (73–100)	99 (99–99)	95 (72–99)	99 (99–99)
Shock	44	3.0	77 (62–88)	99 (99–99)	64 (44–81)	98 (97–99)	73 (54–86)	99 (98–99)

NPV: Negative predictive value, PPV: Positive predictive value, CI: confident interval

Condition	Agreement (%)	Cohen κ statistic
Sepsis	83	0.46
Pneumonia	91	0.48
Aspiration	99	0.58
Pancreatitis	99	0.78
Shock	97	0.40

Table 5   Agreement percentage and Cohen κ Statistics between Manual vs. Electronic data extraction in the validation cohort

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Appendix-Table 1   DDQB Search Text used for each condition

Condition	Sub condition	Algorithm
Sepsis	Empiric anti-microbial	Any 2 of [(Heart rate > 90/min at least 2 times in 1 hour), (Respiratory rate >20 at least 2 time in 1 hour), (body temperature <36°C OR >38°C), (WBC count <4000 cell/mm^3 OR >12000 cell/mm^3)] occurring within 24 hour time window of each other **AND** antimicrobial administration* (excluding Cefazolin)
Pneumonia	Pneumonia	Clinical Note contain ("pneumonia", "aspiration pneumonia", "community acquired pneumonia", "hospital acquired pneumonia", "hospital-acquired pneumonia", "healthcare-associated pneumonia", "healthcare acquired pneumonia", "lung infiltrate", "lung infiltrates", "lung infiltr%", "new lung infiltr%") **AND NOT** contain ("not" Same sentence as "pneumonia", "no" Same sentence as "pneumonia", "no evidence" Same sentence as "pneumonia", rule out" Same sentence as "pneumonia", "unlikely" Same sentence as "pneumonia", "differential" Same sentence as "pneumonia", "vaccine" Same sentence as "pneumonia", "unremarkable" Same sentence as "pneumonia", "history of hospitalization" Same sentence as "pneumonia", "less likely" Same sentence as "pneumonia", "no" Same sentence as "lung infiltrate", "no" Same sentence as "lung infiltrates", "hx of aspiration pneumonia", history of pneumonia", "pneumonia risk", "recently diagnosed pneumonia", "recent pneumonia", "history of recurrent pneumonia") in section Diagnosis, Problem Oriented Hospital Course
Aspiration	Aspiration	Clinical Note contain ("aspiration", "aspirated", "possible aspiration", "aspiration pneumonia") **AND NOT** contain ("wound" Same sentence as "aspiration", "wound" Same sentence as "aspirated", "needle" Same sentence as "aspiration", "ultrasound" Same sentence as "aspirated", "ultrasound" Same sentence as " aspiration", "recent" Same sentence as " aspiration", "diagnostic" Same sentence as " aspiration", "therapeutic" Same sentence as "aspiration", "negative" Same sentence as "aspirated", "negative" Same sentence as "aspiration", "bone marrow" Same sentence as "aspiration", "bone marrow" Same sentence as "aspirated", "knee" Same sentence as "aspiration", "knee" Same sentence as "aspirated", "shoulder" Same sentence as "aspiration", "ankle" Same sentence as aspiration", "ankle" Same sentence as "aspirated", "joint" Same sentence as "aspiration", "joint" Same sentence as "aspirated", "arthritis" Same sentence as "aspiration", "renal" Same sentence as "aspiration", "cyst" Same sentence as "aspiration", "no" Same sentence as "aspiration", "not consistent" Same sentence as "aspiration", "precaution" Same sentence as "aspiration", "no evidence" Same sentence as "aspiration", "no sign" Same sentence as "aspiration", "increased risk of" Same sentence as "aspiration", "abscess" Same sentence as "aspiration", "rule out" Same sentence as " aspiration", "concern" Same sentence as "aspiration", "aspiration precaution", "aspiration precautions", "hx of aspiration", "history of aspiration", history of aspiration pneumonia") in section Diagnosis, Problem Oriented Hospital Course
Acute pancreatitis	Pancreatitis	(Clinical Note contain ("pancreatitis", "acute pancreatitis", "pancreatitis" Same paragraph as "abdominal pain", "pancreas" Same sentence as "infection") **AND NOT** contain ("history of" Same sentence as "acute pancreatitis", "hx of" Same sentence as "acute pancreatitis", "no laboratory evidence" Same sentence as "panc%", "do not support" Same sentence as "panc%", "transplant" Same sentence as "panc%", "suspect" Same sentence as "panc%", "prior" Same sentence as "panc%", "not concerning" Same sentence as "panc%", "less likely" Same sentence as "panc%", "no obvious" Same sentence as "panc%", "risk for" Same sentence as "panc%", "mass" Same sentence as "panc%", "no evidence" Same sentence as "pancreatitis") in section Diagnosis, Problem Oriented Hospital Course) AND (serum amylase >150 mg/dL OR serum lipase >140 mg/dL)
Shock	shock	((Systolic blood pressure ≤90 **AND** Shock Index(HR/systolic blood pressure) >1 at least 2 times in 1 hour) **AND** this condition occur at least 2 hours in 1 day) OR Need for continuous vasopressor infusion (any dose of norepinephrine, epinephrine or vasopressin and dopamine >5 mcg/kg/min)

Appendix-Table 2　ICD-9 code for acute condition

Condition	ICD-9 Code
Sepsis	20.2, 22.3, 3.1, 38, 38, 38.1, 38.1, 38.11, 38.19, 38.2, 38.3, 38.4, 38.4, 38.41, 38.42, 38.43, 38.44, 38.49, 38.8, 38.9, 415.12, 422.92, 449, 54.5, 785.52, 995.91, 995.92
Pneumonia	480.0, 480.1, 480.2, 480.3, 480.8, 480.9, 481, 482.0, 482.1, 482.2, 482.30, 482.31, 482.32, 482.39, 482.40, 482.41, 482.49, 482.81, 482.82, 482.83, 482.89, 482.9, 483.0, 483.1, 483.8, 484.1, 484.3, 484.5, 484.6, 484.7, 484.8, 485, 486
Aspiration	507, 507.0, 507.1, 507.8
Acute pancreatitis	577.0
Shock	785.5, 785.5, 785.51, 785.52, 785.59, 958.4, 995, 995.4, 995.6, 995.6, 995.61, 995.62, 995.63, 995.64, 995.65, 995.66, 995.67, 995.68, 995.69, 998