Enhanced Screening and Research Data Collection via Automated EHR Data Capture and Early Identification of Sepsis

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Abstract
Clinical research in sepsis patients often requires gathering large amounts of longitudinal information. The electronic health record can be used to identify patients with sepsis, improve participant study recruitment, and extract data. The process of extracting data in a reliable and usable format is challenging, despite standard programming language. The aims of this project were to explore infrastructures for capturing electronic health record data and to apply criteria for identifying patients with sepsis. We conducted a prospective feasibility study to locate and capture/abstract electronic health record data for future sepsis studies. We located parameters as displayed to providers within the system and then captured data transmitted in Health Level Seven (HL7) interfaces between electronic health record systems into a prototype database. We evaluated our ability to successfully identify patients admitted with sepsis in the target intensive care unit (ICU) at two cross-sectional time points and then over a 2-month period. A majority of the selected parameters were accessible using an iterative process to locate and abstract them to the prototype database. We successfully identified patients admitted to a 20-bed ICU with sepsis using four data interfaces. Retrospectively applying similar criteria to data captured for 319 patients admitted to ICU over a 2-month period was less sensitive in identifying patients admitted directly to the ICU with sepsis. Classification into three admission categories (sepsis, no-sepsis, and other) was fair (Kappa .39) when compared with manual chart review. This project confirms reported barriers in data extraction. Data can be abstracted for future research, although more work is needed to refine and create customizable reports. We recommend that researchers engage their information technology department to electronically apply research criteria for improved research screening at the point of ICU admission. Using clinical electronic health records data to classify patients with sepsis over time is complex and challenging.

Keywords
severe sepsis, critical care, electronic health records (EHR), Health Level Seven (HL7)

Date received: 22 December 2018; revised: 1 March 2019; accepted: 20 April 2019

Introduction
Sepsis—“a life-threatening organ dysfunction caused by a dysregulated host response to infection”—is a significant public health concern and major contributor to morbidity and mortality (Singer et al., 2016, p. 801). Approximately 19 million people develop sepsis worldwide each year, one in three die during the year after hospitalization, and one in six have persistent impairments (e.g., physical, cognitive, psychological, and
immature methods for retrieving and mining EHR data, standardization in terms used by providers. There are no research to be conducted. One major issue is a lack of for a research study will vary based on the proposed may limit research use. The degree of validation needed documenting clinical care, variations across systems patient care'' (p. 626). Although EHR is standard for data fields accurately and comprehensively capture nuances of their EHR system and “the degree to which suggested that researchers become familiar with the several issues pertaining to the quality of EHR data and costs) in their review of 126 studies. They discussed over the past decade. There has been a trend to move away from simply using administrative data sets (e.g., billing/claims data) to more fully engaging the capabil- ities of EHR for outcomes research. Dean et al. (2009) were the first to systematically review the use of EHR systems in the United States for health outcomes research. The authors defined health outcomes broadly (e.g., comorbidities, risk factors, medical care utilization, diagnostic testing, patient-reported data, adverse events, and costs) in their review of 126 studies. They discussed several issues pertaining to the quality of EHR data and suggested that researchers become familiar with the nuances of their EHR system and “the degree to which data fields accurately and comprehensively capture patient care” (p. 626). Although EHR is standard for documenting clinical care, variations across systems may limit research use. The degree of validation needed for a research study will vary based on the proposed research to be conducted. One major issue is a lack of standardization in terms used by providers. There are no standard methods for retrieving and mining EHR data, although implementation and use of standard terminol- ogy (e.g., Systematized Nomenclature of Medicine-Clinical Terms, National Health Information Network, and others) are helping to reduce variability for data coding and capture (Dean et al., 2009; Jensen, Jensen, & Brunak, 2012). The use of EHR data is subject to selection bias and confounding. Some studies that con- trolled for potential selection bias and confounding pri- marily used multivariate regression analysis, some used matching and stratification, and only one used propen- sity score methods. It was observed that many studies also required collection of supplemental data (e.g., patient reports such as quality of life surveys), and it was suggested that integration of such data into future EHR systems could improve assessments by providers and researchers (Dean et al., 2009).

A more recent review by Lin, Jiao, Biskupiak, and McAdam-Marx (2013) identified 96 articles using EHR for research that includes health outcomes. They describe common research issues pertaining to data location and format. For example, free-text data may be difficult to locate and retrieve. One way to overcome this problem is with the use of Natural Language Processing (NLP) to search for key terms within text documents. Only two studies in their review used this approach. One examined recurrent depression and the other exam- ined records for postoperative complications. NLP will be an important method for future research, but much more pioneering work from experts in the field will be needed to design and validate NLP concepts used to assess outcomes and exposures (Lin et al., 2013). The external validity of any research findings using EHR data depends on the experimental design and accuracy of the data retrieved. EHR, even different versions from the same developer, differ because they are customizable to meet the needs to each facility and specific depart- ments within a facility.

EHR systems are designed for clinicians at the point of care and are not designed for research. Thus, there is often a redundancy built into the systems for ease of clinical use by allowing multiple locations for entering and retrieving information (Terry et al., 2010). Terry et al. (2010) categorized 285 abstracts of EHR studies in primary care and provided a “primer” to help researchers planning to engage in EHR research in avoiding pitfalls. They identified few studies focused on data quality and even fewer focused on ethics and privacy in using EHR data for research. The authors shared five helpful considerations for researchers planning to use EHR data: (a) data may be entered by providers in various locations, (b) data may be entered in various formats, (c) data may be entered by providers using inconsistent terms, (d) data may not be readily search- able, and (e) data not required for clinical care may be missing (Terry et al., 2010). They also discussed five

Review of Literature

The use of EHR for research has become more frequent over the past decade. There has been a trend to move away from simply using administrative data sets (e.g., billing/claims data) to more fully engaging the capabilities of EHR for outcomes research. Dean et al. (2009) categorized 285 abstracts of EHR studies across various locations, and (b) data may be entered in various formats, (c) data may be entered by providers using inconsistent terms, (d) data may not be readily search- able, and (e) data not required for clinical care may be missing (Terry et al., 2010). They also discussed five
levels of data extraction, with each level increasing in complexity. The first three are all data queries: (a) predeter-
determined, (b) customizable, and (c) advanced custom-
able. The EHR system usually allows for users to gen-
erate these queries with more advanced queries using Boolean logic. The last two are as follows: (d) struc-
tured query language (SQL) interface and (e) data
extraction and analysis with database tools. These higher
level forms of data abstraction require collaboration
with providers, researchers, and information technol-
ogy professionals. Researchers will need the EHR’s entity
relationship diagram to understand the relationships
among the EHR data files (Terry et al., 2010).

Many challenges have been identified in regard to
using EHR data for research purposes. These challenges
also include processes to assure the availability of accu-
rate and valid data needed for the specific research project
as well as the use of safeguards and privacy in data
mining (Jensen et al., 2012). The Health Information
Technology for Economic and Clinical Health
(HITECH) Act of 2009 encourages the use and develop-
ment of health information technology—improving
health by making the EHR accessible to care providers,
researchers, and public health workers (Blumenthal,
2010). As health information technology is more uni-
formly adopted, terminology becomes standardized,
and systems become more integrated, so that research
using EHR will allow linkage of information to advance
care and provide individualized patient-centered preci-
sion medicine (Collins & Varmus, 2015). Currently,
research involving EHR data requires careful review of
the data available while assessing the ability to capture
that data electronically and validating the data.

**Purpose**

The authors conducted a feasibility study to prospect-
ively abstract EHR data for sepsis patients. The goals
of this study were to (a) explore infrastructure for cap-
turing data, (b) identify medical intensive care patients
admitted with sepsis, and (c) validate our ability to cor-
rectly identify patients with sepsis electronically based on
specific criteria.

**Methods**

This prospective feasibility study examined the local
infrastructure for capturing EHR data, applied coding
rules and restrictions to electronically identify patients in
the medical ICU (MICU) with sepsis, captured EHR
data from data streams (described below), and validated
automated sepsis classification in two small cross-
sectional samples and one large sample gathered or “cap-
tured” over 2 months. This study was approved by the
university and hospital institutional review boards.

Individual informed consent was waived by the institu-
tional review board. All identifiable EHR data for this
project remained behind the hospital firewall, accessible
only to the research team. Methods to identify the study
population, role of the team, data collection, and data
analysis follows.

**Study Population**

The target population was patients admitted with sepsis
to a 20-bed MICU in an academic southeast U.S. med-
ical center. Initially, our focus was the combination of
EHR data fields, variables, and infrastructures, rather
than patients. Next, we identified sepsis patients using
the following automated EHR programmed criteria:

- Admitted directly to the medical intensive care unit
- Elevated white blood cell count >12,000 or <4,000
- Temperature > 38.3°C or < 36°C
- Receiving antibiotics. We restricted to common
  antibiotics used for sepsis patients, including
  Piperacillin/Tazobactam, Moxifloxacin, Ceftriaxone,
  Clindamycin, Azithromycin, Gentamycin, and
  Vancomycin.
- Admission history and physical data that used the
  following terms: sepsis, septic shock, pneumonia,
  community-acquired pneumonia, health-care-asso-
  ciated pneumonia, bacteremia, urosepsis, and urinary
  tract infection.

These criteria are similar to the criteria used to develop
the Sepsis-3 definitions using EHR data as well as prior
definitions (Levy et al., 2003; Shankar-Hari et al., 2016;
Singer et al., 2016). We sought to identify patients with
suspected sepsis to facilitate additional screening by
study personnel prior to seeking informed consent.

Individual chart review was targeted to classify patients
into three groups, namely: Group 1: patients who were
not admitted directly to the ICU, who were in the ICU
for less than 48 hours, or were younger than 18 years old;
Group 2: directly admitted to ICU with sepsis; and
Group 3: directly admitted to the ICU without sepsis.
Specifically, we manually reviewed identified EHR for
the following inclusion criteria:

- ICU length of stay greater or equal to 48 hours
- Age greater than 18 years
- Direct MICU admission
- Possible sepsis code (based on chief complaint and
  history and physical)
- A positive Systemic Inflammatory Response Score
  (SIRS) at admission (at least 2 of 4)
- Individual positive or negative SIRS components
  (white blood cell, Temperature, heart rate, respiratory rate)
The presence of antibiotics at admission
Positive cultures at admission

Exclusion criteria included:

- Patients who were not admitted directly to the ICU
- Patients who were in the ICU for less than 48 hours
- Patients younger than 18 years old

When exclusion criteria were identified, full screening was not collected. These excluded patients were classified as Group 1, the excluded group.

**Study Team**

We used a multidisciplinary team. The principal investigator, R.U., has a background in critical care and sepsis research. C.C. had worked as a nurse in MICU and routinely used the Cerner Millennium® EHR (Cerner©2016, Cerner Corporation, North Kansas City, MO), and C.I. is a data systems analyst with expertise in programming and working with the EHR systems. R.U. developed the list of variables to assess (Table 1) and worked with C.C. to locate each variable within the EHR system. They communicated these details to C.I., who used data mining techniques to assess our ability to capture the variables in Table 1 and to electronically identify patients admitted to the MICU with sepsis using the criteria identified earlier. M.S. assisted with initial cross-check validation. M.S. was an MICU Team Leader who assisted with chart reviews. R.U. and M.S. reviewed automatic classification from the prototype against clinical records in Cerner as noted above to determine group classification. R.J. was MICU Nurse Manager and assisted with early conceptualization and understanding the unit’s existing work in sepsis surveillance. J.S. was the MICU Comedical Director and provided consultation for later phases of the project.

**Data Collection**

The goals of this study were to (a) explore infrastructure for capturing data, (b) identify MICU admitted with sepsis, and (c) validate our ability to correctly identify patients with sepsis based on specific criteria. First, we developed a spreadsheet with a list of parameters (Table 1) to extract from the Cerner database. To explore the infrastructure for capturing data, we reviewed the front-end user display and provided the analyst with our observed location of each parameter. We tested accessibility of the data and created an infrastructure to capture the data for reports while not interfering with EHR performance for front-end users. We created a multidimensional data set and flat tables for data visualization and aggregation, a prototype database (PDB) as shown in Figure 1. All of these data remained protected behind the hospital firewall. We manually compared accessibility of each parameter—as displayed within the PDB and as displayed to front-end users in Cerner—on the spreadsheet until we observed nothing new (had reached saturation). We provided feedback to the analyst for adjustments to the PDB as needed.

Next, to identify patients in the MICU with sepsis at two time points, the analyst applied sepsis criteria (described under study population) to the list of patients on the MICU census while two nurses reviewed the census and made visual comparisons. To validate our ability to correctly identify patients with sepsis, we conducted individual chart review and compared manual review with computer classifications applied within the PDB. We used approaches used previously (Figure 1) to capture data using Health Level Seven (HL7), a standard language for integrating and exchanging electronic health data to mediate the flow of information from various hospital systems (Health Level Seven® International). For example, we used the following HL7 message types between interfaces to capture health system data streams:

- ADT (Admission, Discharge, Transfer) for demographic and coding information;
- ORU (Observation Result) for laboratory results, vital signs;
- RDE (Pharmacy/Treatment Encoded Order) for medication/antibiotics information; and
- MDM (Medical Document Management) for transcription documents like H&P.

SQL was used to extract data from Cerner Millennium® (health information system in Figure 1). We pulled parameters (target variables described in Table 1) and used filters and rules (as detailed in the inclusion criteria above) to identify patients with sepsis. We also tested methods to de-identify the data by assigning a unique identification number which is meaningless to the Cerner Millennium® database and cannot be used to search for patient information outside of the PDB.

**Data Analysis**

We made visual comparisons to examine data presented in the PDB with the data displayed within the Cerner EHR system. We evaluated individual records and made comparisons until we reached saturation of the findings for variables in Table 1 (n = 5 EHR records) when examining the ability to capture a selected variable. Cross-sectional verification also did not require data analysis. The analyst applied filters and codes to identify patients with sepsis to generate a list of patients with sepsis at two time points. Two nurses compared that
list with the list of patients with sepsis on the unit census. Next, longitudinal data captured in the PDB over 2 months were classified into the three groups as described earlier. Kappa statistics were calculated comparing automatic computer classifications with chart review classifications.

**Results**

**Ability to Abstract EHR Data**

A PDB was successfully created behind the hospital firewall. The data were displayed in a series of tables through a password-protected portal. The team was provided with a link to the portal for ease of access within the hospital’s intranet. One table included identifiable information (i.e., each patient’s medical record number, a linking identification number, hospital and ICU admission and discharge dates, calculated hospital and ICU length of stay, chief complaint, name, gender, age, and DOB) to enable comparisons of data within the hospital EHR against the data that were captured and displayed in the PDB tables. A majority of the variables in Table 1 were accessible using an iterative process to locate them. There were three versions of the PDB over the course of the entire project. One important finding was that corrected laboratory values (incorrect values that were corrected by the laboratory) were not identified by this approach. We only identified them by examining data for inconsistencies in values that were beyond normal range.
Many of the data points were not easily accessible from either front-end applications (such as the nursing Kardex, which is a custom hospital program) or back-end queries (from the Cerner Database and requiring Oracle Procedural Language/SQL, Cerner Command Language, and Cerner's Visual Developer Tool). For example, data points that were difficult to access that appeared on the nursing Kardex but were accessible with additional coding were ICU admission and discharge dates and ICU discharge destination. Data points that were challenging for a variety of reasons included laboratory values, mechanical ventilation settings, varying location of vital sign parameters, and medications. Data points that were not accessible were invasive devices, blood products, code blue, and diet. Free-text documents such as the H&P were accessible as a complete document for review, but we did not use NLP to pull or locate details from this document and reviewed them in context. Culture results were also formatted as Cerner encrypted text but were not accessible within the PDB.

**Testing Computer Classification of Patients With Sepsis in Cross-Sectional Samples**

We performed two cross-sectional evaluations of our ability to identify patients with sepsis who were in the ICU at that time. During the first assessment, we

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**Figure 1.** Conceptual data flow design. The methods used to abstract data from health systems to a prototype database (PDB) behind the hospital firewall are depicted. HL7 denotes Health Level Seven® International interface language. A password-protected portal to the PDB allowed team access to review and compare captured data to health system data. Later phases of this project explore secure methods of extracting de-identified data from the PDB for statistical analysis. HIS = health information system; LIS = laboratory information system; PIS = pharmacy information system; POCT = point-of-care testing system; MRS = medical record system; WBC = white blood cell.
successfully electronically identified 5 of 6 patients with sepsis (among 19 in the target unit). One patient with COPD was mistakenly identified as having sepsis by computer programming possibly related to antibiotic use and respiratory rate. One patient with septic endocarditis was identified by computer programming and initially missed by chart review until further electronic documents were manually reviewed. Programming changes were made prior to the next assessment. During the second assessment, all patients who had sepsis (among the 17 patients in the target unit) were correctly identified as having sepsis and two patients were incorrectly identified as having sepsis (false positive). One of those patients had an infection, but no SIRS and the other patient had an altered mental status for reasons other than severe sepsis. Altered mental status is a frequent occurrence in sepsis, so these terms were included in the chief complaint evaluation by the computer program. Patients with sepsis were successfully identified using four data interfaces (health information system, laboratory information system, pharmacy information system, and medical record system).

Testing Computer Classification of Patients With Sepsis in Longitudinal Data

As described earlier, a relational PDB was developed behind the hospital firewall to collect data streams from hospital system interfaces over a 2-month period. Table 2 shows computer classification and chart review classification among 319 patients admitted during this period. Percentage agreement was 87.5%, 16.7%, and 59.0% between computer and chart classification among chart confirmed cases with 208, 72, and 39 cases classified in Group 1 (patients who were not admitted directly to the ICU, who were in the ICU for less than 48 hours, or were younger than 18 years old), Group 2 (directly admitted to ICU with sepsis), and Group 3 (directly admitted to the ICU without sepsis), respectively. Although the overall table agreement was fair (Kappa .39), the groups of most interest (sepsis/suspected sepsis at ICU admission) had poor agreement. Feedback was given to the programmer to improve classification/coding to identify sepsis patients. Classification using a single time point (upon admission to the ICU) was more accurate than classifying patients based on data over time due to the changing nature of many classification variables over time (e.g., antibiotics).

Discussion

This feasibility project was an iterative process requiring identification of data streams to capture specific data points (parameters), verify our ability to correctly and electronically identify patients with sepsis by manual EHR review, and refine parameter search terms until parameters and patients with sepsis were accurately identified. Although the HL7 standard is widely used in health care, existing barriers remain in seamlessly extracting data from the EHR in an analyzable format.

Abstraction Data From the EHR

Clinical EHR data, like administrative data sets, are not created for research purposes and present challenges (Hersh et al., 2013). This project was designed to test the ability to pull data from the EHR specifically for the purposes of future research and to supplement directly collected bedside information in experimental and nonexperimental research (from consenting patients). The majority of data abstraction in this feasibility study required higher level abstraction techniques (SQL and above) as described by Terry et al. (2010). The

Table 2. Classification of EHR Data for 319 MICU Patients Admitted Over a 2-Month Period.

| Classification       | Defined                                | Automatically classified | Chart review classification | Agreement |
|----------------------|----------------------------------------|-------------------------|-----------------------------|-----------|
| Group 1              | Not directly admitted to MICU from the ER or admitted for less than 48 hours | 209 (65.5%)" | 208 (65.2%) | 182 (87.5%) |
| Group 2              | Directly admitted to MICU with sepsis or suspected sepsis | 16 (5%) | 12 (16.7%) |
| Group 3              | Directly admitted to MICU without sepsis at admission | 94 (29.5%) | 39 (12.2%) | 23 (59.0%) |

Note. The Kappa statistic of .39 (32–46) comparing automated versus manual classifications. This statistic indicates fair agreement, but these results are driven by the large number in Group 1. Considering chart review as the gold standard, percentage agreement is shown between computer classification and chart review in the third column. The agreement is poor when comparing the ability to distinguish between those with and without sepsis at admission. This may be explained by chart review allowing for a detailed review of the H&P, Systemic Inflammatory Response Score, antibiotics, and cultures at the time of admission. MICU: medical ICU; ER: emergency room; EHR: electronic health records.

"Ten patients had missing records and could not be automatically classified. They were excluded (Group 1).
process of creating the PDB to access selected parameters required a team and several iterations, which is consistent with other projects evaluating the use of EHR for research (Apte et al., 2011). The team members spent extensive time validating the data, and a rapid PDB visualization tool was useful during the design sessions/team meetings. Most of the challenges we detected have been experienced by others.

**Parameters location.** There are multiple ways that nurses can document vital signs as well as other parameters. Data points for the same laboratory test may originate from a point-of-care system or the laboratory information system. Further, heart rate can be abstracted from an EKG monitor, pulse oximeter, or manually entered. In addition, vital signs may reside in fields specific to ICU vital signs rather than routine vital signs taken in a ward. It is challenging when all components of calculated values are not present at the same time. For example, SIRS scores include four components, but each component is not collected with the same frequency or timing. Capturing the vital signs data was one of the most challenging parts of the project. It is important for clinical researchers and IT to work together to specify which variables are to be used for research, and protocol congruent rules should be put in place for handling missing data to prevent statistical imputations (that may regress to the mean) when real data (possibly within even a few minutes) are available.

**Multiple parameter measures.** The problem of which values to select when there are multiple measures taken on the same day is not unique to EHR studies. Operational designations need to be made in advance and clearly specified in clinical trial protocols. For example, studies that examine longitudinal data may collect data at a single time point each day (e.g., 8:00 a.m.), and in so doing miss events that occur at other time points. One way we accounted for variability is to capture it by recording daily minimum and maximum values for parameters, in addition to a standard time. We were able to generate this information in PDB reports. Studies that examine only one time point may miss important variability.

**Parameter format.** As mentioned in the “Introduction” section, clinicians often document in more than one location, and free-text notes allow them flexibility to express case details. Free text is commonly used, is heterogeneous, and can be challenging to analyze. NLP and machine learning techniques are used to extract text data (Jensen et al., 2012). For the purpose of our project, we pulled full reports which could be viewed in context by researchers in prospective experimental or nonexperimental clinical bedside research.

**EHR system changes.** EHR updates can be required by institutions (programmed internally) to allow for capture of Core Measures that institutions must report or based on unit specific needs. This may lead to differences in the way that providers document or differing internal methods of capturing the data. Change can also arise during system upgrades and updates from the makers of EHR systems or due to institutional decisions to add or remove packages (e.g., during this project an add-on package that enabled daily APACHE II calculation was not repurchased). It is unknown how often EHR changes occur—internally or externally—but technology is rarely static. Investigators designing projects designed to collect data from the EHR will be impacted by changes and should work closely with IT to review changes frequently.

**Electronic Detection of Patients With Sepsis**

Our second cross-sectional review was more sensitive, as it identified more patients as having sepsis than actually had sepsis, an increase in false positives. We could have further adapted the rules, but we preferred to have more false positives in order to prevent missing any potential patients who might have sepsis. Although we only evaluated our ability to identify patients with sepsis for screening, the next step would be to establish an automatic notification system for research. Others have electronically identified patients using investigator-designed algorithms to screen for recruitment and have thereby increased their recruitment efficiency and the sensitivity of identifying patients (Cardozo, Meurer, Smith, & Holschen, 2010; Herasevich, Pieper, Pulido, & Gujic, 2011). Cordozo et al. (2010) increased the sensitivity of screening from 5.9% to 100% after implementing automated electronic record screening versus the prior method of patients screening by paging physicians. Herasevich et al. (2011) doubled research participant recruitment from four patients per month to eight patients per month after implementation of the automated “septic shock sniffer” to identify septic shock patients using the EHR. Although their study coordinators had access to all aspects of the EHR and had used it for screening, they often used physician notes for their preliminary evaluation and their review of physiologic variables may have been limited (Herasevich et al., 2011). Time and motion studies have shown reduced screening time per patient by using an electronic screening tool—reduced from 18 minutes to less than 3 minutes (Thompson, Oberteuffer, & Dorman, 2003). Developing and using automated systems within the EHR to identify potential study participants should become a more commonplace in sepsis studies. Increased recruitment efficiency will shorten the time needed to complete clinical research (experimental
and nonexperimental studies) and will allow for more timely dissemination of findings.

The international classification of diseases (ICD) is commonly used to identify research records. These codes are typically not available at the point of care for most institutions, as they are assigned upon discharge by medical record coders based on provider assessments and specific disease criteria. These codes were designed for administrative purposes rather than research, but validated methods are available for retrospective research to identify patients with sepsis (Fleischmann-Struzek et al., 2018; Iwashyna et al., 2014; Jolley et al., 2015). Some institutions assign ICD codes upon admission and discharge, so using ICD coding may also be beneficial in prospective research in some settings.

**Hospital-Wide Sepsis Alert Implementation**

Sepsis is an important problem and forward-thinking institutions put systems in place to help them improve prevention, early detection, and treatment of sepsis. During this project, the hospital implemented a sepsis detection system called the St. John Sepsis Agent®, which “crawls/iteratively searches” through the EHR and sends alerts to nurses when SIRS and organ failure criteria are met (Amland & Hahn-Cover, 2016; Amland, Haley, & Lyons, 2016). We reported details of the early alert system’s implementation with a focus on the SIRS and MODS details among the patients in Table 2 who were admitted directly to MICU with and without sepsis (Umberger, Indranoi, Simpson, Jensen, & Shamiyeh, 2013).

As the alert system was implemented, trigger parameters were modified to reduce the number of false-positive alerts. Each alert required contacting providers. Issues related to work flow following hospital-wide implementation of similar systems have been reported (Guidi et al., 2015), and the hospital did experience some of these workflow issues. J.S. spent a year facilitating meetings throughout the hospital to improve local implementation of the system (e.g., addressing false positive alerts, improving work flow-related issues, and preventing desensitization with alerts), as well as developing a sepsis bundle process. A sepsis coordinator was hired to oversee the sepsis program with the medical director. Among other duties, this coordinator is responsible for monitoring and improving the SEP-1 Core Measure performance (Drake, 2015). The development of a specific sepsis initiative led to the creation of a performance improvement data infrastructure focused on sepsis metrics. The sepsis team encountered similar challenges as those outlined in this article in terms of extracting correct and relevant information from the EHR. This suggests that any further work on processes to reliably extract sepsis data from EHRs for research purposes may simultaneously have a positive impact on hospital performance improvement activities.

**Limitations**

In our project, we used data streams and evaluated the ability to abstract a broad range of data types over time. We also examined our ability to capture variability (minimum and maximum range) for several important variables that are used to evaluate severity of illness via tools like APACHE. We did not apply our review in a real-time fashion, nor did we define the sensitivity and specificity of our approach during this pilot feasibility study.

We used the SIRS criteria for this project because the SIRS criteria were part of the most recent consensus sepsis criteria at the time of implementation of this project (Levy et al., 2003). This study began before Sepsis-3 and qSOFA criteria were released (Singer et al., 2016).

**Implications for Practice**

Electronic methods may help facilitate earlier sepsis identification by using a combination of NLP and risk stratification tools to refine sepsis alerts using smart algorithms that consider the heterogeneity and diversity of this population. Sepsis alert systems can have high sensitivity (93%) and specificity (98%), yet still have a low positive predictive value (21%; Alsolamy et al., 2014). Implementation of automated alert systems must be designed with careful attention to work flow and prevention of potential alarm fatigue. The development of artificial intelligence and deep machine learning will allow for real-time data stream monitoring to better predict sepsis in the future (Kamaleswaran et al., 2018; Nemati et al., 2018) Real-time data gathering with precise data displayed for critical decision support will be needed for clinicians. Researchers working with IT professionals can readily identify patients with sepsis with minimal programming; however, data abstraction for research is more time consuming and programmer intensive. As hospitals and outpatient clinics become more connected, these methods may facilitate more complete long-term data collection, thus helping to reduce fragmentation of care after sepsis.

**Conclusions**

Although providers are able to easily view EHR data for clinical care, the abstraction of data directly from EHR systems for research purposes remains a challenge. Despite limitations, improving direct data capture methods can assist in targeting potential clinical trial participants and reduce the burden of data collection. More research is needed to determine the best methods for automatically identifying patients with sepsis.
Authors’ Note

The aspects of this project have been presented at (a) Sigma Theta Tau Gamma Chi Chapter’s Research Day in Knoxville, TN, (b) the University of Tennessee Medical Center in Knoxville, TN, and (c) the Society of Critical Care Medicine in San Francisco, CA.

Acknowledgments

The authors would like to acknowledge the support of Ms. Camille Coleman, MSN, RN, CCRN, for her assistance with the project as a part of a research immersion course. She assisted the R.U. with locating data within Cerner and the cross-sectional assessments. J.S. was the Medical Critical Care (MCC) Medical Director, R.J. was the MCC Nurse Manager, and M.S. was the MCC Team Leader at the time this project was designed and conducted. The authors thank Dr. Richard Redfearn (Director of Scientific Writing, Office of Research, University of Tennessee Health Science Center) for editing the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was funded by the Health Information Technology and Simulation Research Unit at the University of Tennessee, Knoxville, TN.

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