REFERENCES

1. Chan PS, Jain R, Nallmothu BK, et al: Rapid response teams: A systematic review and meta-analysis. *Arch Intern Med* 2010; 170:18–26
2. DeVita MA, Smith GB, Adam SK, et al: "Identifying the hospitalised patient in crisis"—A consensus conference on the afferent limb of rapid response systems. *Resuscitation* 2010; 81:375–382
3. Wunderink RG, Diederich ER, Caramez MP, et al: Rapid reponse team-triggered procalcitonin measurement predicts infectious intensive care unit transfers. *Crit Care Med* 2012; 40:2090–2095
4. Jensen JU, Hein L, Lundgren B, et al; for The Procalcitonin And Survival Study (PASS) Group: Procalcitonin-guided interventions against infections to increase early appropriate antibiotics and improve survival in the intensive care unit: A randomized trial. *Crit Care Med* 2011; 39:2048–2058

How can we best use electronic data to find and treat the critically ill?*

Timely intervention in sepsis is important. Mortality increases significantly for each hour of delay in administering antibiotics to patients in septic shock (1). However, delays in administration of antibiotics and failure to provide other guideline-recommended care for sepsis are common (2). The ability for automated decision support systems to assist with adherence to best practice seems promising.

In this issue of *Critical Care Medicine*, Hooper et al (3) designed a thoughtful trial to evaluate the clinical effect of an electronic support system, which used computer-derived patient data to notify clinicians when patients admitted to the medical intensive care unit had met systemic inflammatory response (SIRS) criteria.

In this study's intervention group, clinicians received text messages via pager that patients had met SIRS criteria. A flag was placed next to the name of the patients in the intervention group who had met SIRS criteria which was visible to all clinicians.

There was no difference in the primary endpoint of time to administration of new antibiotics, nor in other measured clinical outcomes including intravenous fluids given, length of stay, or mortality.

Ultimately, the utility of automated alert systems, like all health IT solutions, depends on the degree of clinical necessity, the complexity of data integration required, and the ability to outperform or improve the performance of their human counterparts. In this study, Hooper et al faced several challenges in demonstrating a benefit in the alert system: 1) intensive care physicians are already acutely sensitive to the detection of SIRS/sepsis; 2) detection of SIRS has limited specificity for detection of sepsis; and 3) the targeted outcome, earlier antibiotic administration, was already being achieved at a reasonably high rate (4). It is not entirely surprising, then, that the clinical outcomes in this study were not met.

Rather than ringing the death knell for computerized surveillance tools, identification of these challenges provides insight into the types of situations in which these tools may be most useful.

First, a computerized alert system should target an area where physician vigilance is low. A study by Herasevich et al (5), for example, demonstrated the ability of a computerized tool to detect acute lung injury in a setting where clinicians missed nearly 75% of these diagnoses. If the alert system developed by Hooper et al was deployed in environments where sepsis is less common and physicians' sensitivity to the diagnosis of sepsis is correspondingly lower (i.e., patients on the general medical wards), the outcomes may be more striking, as has been suggested in a study of computerized alerts for sepsis for non–intensive care unit patients (6).

Second, this type of intervention may demonstrate greater efficacy if it is able to cull data from disparate sources, both structural and temporal. A system that could integrate a patient's prior culture data, for instance, might be able to provide custom antibiotic recommendations along with the SIRS notification. Whereas some investigators have already incorporated basic free-text analysis (5), full realization of this potential may require even more sophisticated natural language processing tools, which can extract clinical concepts as well as data from physician notes and reports. Several institutions are already operationalizing such advanced natural language processing tools, and these tools are likely to become increasingly widespread in the coming years (7, 8).

One of the greatest advantages of employing a computational solution is the ability to perform more complex calculations and execute multitiered risk prediction models. Part of the elegance of the current SIRS criteria stems from its simplicity and ease of human calculation. However, a computerized algorithm may benefit from a more complex solution that integrates a larger number of variables to identify impending SIRS at an earlier point in time—a "dynamic approach" as suggested by Nelson et al (9). Such a model could eventually lead to earlier clinical interventions.

Finally, tools that can automatically close an action loop may also help facilitate process improvement. For example, a system which uses natural language processing might not only determine which antibiotics would be optimal for a patient based on prior culture results but also might place an order for those antibiotics with doses based on the patient's creatinine clearance. A clinician could review the orders as the medications are being prepared by the pharmacist. Using systems to automatically close action loops could further accelerate delivery of care and potentially improve delivery of the right medications at the right doses.

As EMRs become increasingly integrated and natural language processing technology continues to advance, the wealth

*See also p. 2096.

Key Words: electronic alerts; natural language processing; sepsis; septic shock; systemic inflammatory response

The authors have not disclosed any potential conflicts of interest.

DOI: 10.1097/CCM.0b013e318256b99b

of data that can be analyzed will soon become overwhelming for any single person. Solutions such as this one serve as proof-of-concept that computerized alert systems can be integrated with clinical workflow, and as the sophistication of these systems continues to improve, undoubtedly so too will the clinical outcomes.

Gaurav Singal, MD
Paul Currier, MD, MPH
Massachusetts General Hospital
Boston, MA

REFERENCES

1. Kumar A, Roberts D, Wood KE, et al: Duration of hypotension before initiation of effective antimicrobial therapy is the critical determinant of survival in human septic shock. *Crit Care Med* 2006; 34:1589–1596
2. Fong JJ, Cecere K, Unterborn J, et al: Factors influencing variability in compliance rates and clinical outcomes among three different severe sepsis bundles. *Ann Pharmacother* 2007; 41:929–936
3. Hooper MH, Weavind L, Wheeler AP, et al: Randomized trial of automated, electronic monitoring to facilitate early detection of sepsis in the intensive care unit. *Crit Care Med* 2012; 40:2096–2101
4. Ferrer R, Artigas A, Levy MM, et al; Edusepsis Study Group: Improvement in process of care and outcome after a multicenter severe sepsis educational program in Spain. *JAMA* 2008; 299:2294–2303
5. Herasevich V, Yilmaz M, Khan H, et al: Validation of an electronic surveillance system for acute lung injury. *Intensive Care Med* 2009; 35:1018–1023
6. Sawyer AM, Deal EN, Labelle AJ, et al: Implementation of a real-time computerized sepsis alert in nonintensive care unit patients. *Crit Care Med* 2011; 39:469–473
7. Zallis M, Harris M: Advanced search of the electronic medical record: Augmenting safety and efficiency in radiology. *J Am Coll Radiol* 2010; 7:625–633
8. Harvey JM, et al: Automated identification of postoperative complications within an electronic medical record using natural language processing. *JAMA* 2011; 306:848–855
9. Nelson JL, Smith BL, Jared JD, et al: Prospective trial of real-time electronic surveillance to expedite early care of severe sepsis. *Ann Emerg Med* 2011; 57:500–504

Identifying the patient at risk of deterioration, intensive care unit admission, or cardiac arrest: Stop predicting, start preventing*

Preventing patient deterioration, unplanned intensive care unit (ICU) admission, or cardiac arrest requires staff education, monitoring of patients, recognition of patient deterioration, a system to call for help, and an effective response. These measures have been described as the "chain of prevention" (1). In-hospital cardiac arrests are often preceded by hypoxia or hypotension that is not treated, and only about 20% of cardiac arrest patients survive to discharge (2, 3). Early recognition, a call for help, and treatment of the deteriorating patient might prevent cardiac arrest or ICU transfer and also identify patients for whom cardiopulmonary resuscitation or ICU transfer is not appropriate. Many hospitals already use an early warning score (EWS) or "calling criteria" based on physiological bedside observations as part of a rapid response team (RRT) system. Indeed, numerous EWS systems are available (4). The EWS is calculated using the sum of points allocated to each vital sign measurement (based on its deviation from "normal"). The response is determined by the total EWS and could include calling a RRT. The medical emergency team (MET) system uses calling criteria; the MET is activated when one or more vital signs reach a predetermined abnormal value (5). The best method of recognition and triggering a response is still unknown. A multicenter cluster randomized trial of the MET system showed an increase in MET calls but no reduction in the prevalence of cardiac arrest, unexpected deaths, or unplanned ICU admissions (6). In a meta-analysis of 18 studies, RRT/MET systems reduced cardiorespiratory arrest rate outside the ICU, but did not lower overall hospital mortality (7). Recent U.S. data suggest that the prevalence of treated in-hospital cardiac arrests is actually increasing (8).

Most current scoring systems have been based on expert clinical opinion. Few have used a formal derivation process to ensure good performance in terms of discrimination and validity. Discrimination is the scores ability to identify at-risk patients. If the score's false-positive and false-negative rates are plotted against each other (a receiver operator characteristic curve), an ideal score would have an area under the receiver operator characteristic curve of 1.0. An ideal score should also be valid in different healthcare settings.

In this issue of *Critical Care Medicine*, Churpek and colleagues (9) have used ward vital signs from a single U.S. center to develop a cardiac arrest risk triage (CART) score. Electronic medical record data collected between 2008 and 2011 from 88 ward cardiac arrest patients, 2,820 noncardiac arrest ICU transfers from a ward, and 44,519 controls were studied retrospectively. The hospital did have a RRT system in place at the time. Multiple logistic regression was used to develop the prediction model. Regression coefficients were then used to create the CART score based on respiratory rate, heart rate, diastolic blood pressure, and age. When compared with the modified EWS, using respiratory rate, heart rate, systolic blood pressure, temperature, and neurology, CART was a better predictor of cardiac arrest (area under the receiver operator characteristic curve 0.84 CART vs. 0.76 modified EWS; $p = .001$), and the need for ICU transfer (area under the curve 0.71 vs. 0.67; $p < .001$) (10). CART identified patients at risk of cardiac arrest a median of 48 hrs before the event at a cutoff with approximately 90% specificity and 50% sensitivity. The use of diastolic blood pressure is unusual for an EWS but in keeping with previous studies on severe infection (11). The ability

*See also p. 2102.

Key Words: hospital rapid response team; in-hospital cardiac arrest; physiologic monitoring

Dr. Subbe consulted for and received honoraria from Philips. Dr. Soar has not disclosed any potential conflicts of interest.

DOI: 10.1097/CCM.0b013e3182546875