Computers in White Coats: How to Devise Useful Clinical Decision Support Software*

When sorrows come, they come not single spies
But in battalions.–Hamlet, IV.v.

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The rate of alarms in clinical care is, well, alarming. Some quality control would be gratefully accepted. In this issue of *Critical Care Medicine*, Chen et al (1) from the critical care redoubt in Pittsburgh report on a combined effort by clinicians and data scientists—results made possible only through fusion of substantial clinical elbow grease and large-scale computing—to address the fundamental challenge of telling true alarms from false. Four clinicians each spent 100 hours (!) inspecting the 973 alarm records analyzed. The result—a computerized decision as to whether the alarm was true or not—promises a clinically significant reduction in alarm frequency with no clinically significant increase in risk to patients. This is not the only article on this topic, but we feel this major work stands apart by pounding home the notion that the hardest part of computer programming to support clinical decisions has nothing to do with computers.

We are all witness to the torrent of new computer algorithms and smartphone apps intended to provide clinical decision support in the care of patients, from multi-lead electrocardiograms to colposcopy. There is little question that they provide additional information to bedside practitioners, but there are so many algorithms and apps now—how do we know which will help? And, with so much promise in this field, many data scientists and app developers are turning toward healthcare—what criteria must they satisfy to develop a quality product?

One vision is that decision support should synthesize new and nonobvious information that can point the clinician in unanticipated directions or serve as a tiebreaker when clinical scenarios are ambiguous. Increasingly, cross-disciplinary teams like Chen et al (1) at Pittsburgh and Carnegie-Mellon gather together with this kind of goal. Now what do they do?

*See also p. e456.

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We—from left to right, a clinical cardiologist, a mathematician, and a new-generation hybrid model—have watched and worked in this field for as many as 15 years. Here is our suggested prescription.

PICK THE RIGHT PROBLEM

This step is the hardest. The problem must be important but tractable, with a reasonable expectation of improving outcomes. Simple as it sounds, this is, in our view, the most common point of failure. Preoccupied in the care of the individual patient, clinicians are frequently too busy to sufficiently explore and carefully identify problems that meet these criteria. It is our opinion that many works in this field are too limited in scope—niche problems may be more tractable than general ones, but one wishes, after all, to do the greatest good. On the other hand, data scientists use the latest analytical tools but have not practiced medicine.

LOOK AT THE DATA

This step is the most time-consuming. Clinicians and mathematicians need to spend hours and hours together looking at the clinical records and time series of physiologic waveform and vital sign records. One goal is to identify with our eyes the features that we wish to quantify—for example, this is how we found reduced variability and transient decelerations prior to neonatal sepsis (2) and validated algorithms to detect neonatal apnea (3). The effort of Chen et al (1) was remarkable, and we are reminded of the similarly heroic work on alarm classification by Drew et al (4).

FEAR NO MATH

This step is the most interesting and fun. We look to the data and other quantitative scientists to reduce the observations of the clinicians to measured variables, often novel. Hu et al (5) used advanced data mining techniques to create Super-Alarms. Hubbard et al (6) and Cohen et al (1) have developed and applied SmartLearning algorithms for mortality prediction in trauma patients, and Johnson et al (7) used Bayesian classifiers for mortality prediction in the ICU. We developed sample entropy to detect the reduced variability and transient decelerations that precede neonatal sepsis (8, 9), and Costa et al (10) extended it to the widely-applied multiscale entropy. (We acknowledge, affirm, admire, and apologize to our many friends and colleagues omitted from this list.)

DO CLINICAL TRIALS

This step is the most nerve-wracking. This is the work that lies ahead for these new alarm algorithms, and it may—no,

should—be guided by recent guidelines, such as Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis checklist (11) for developing, validating, and justifying new algorithms as decision support tools. We note, however, that common metrics to evaluate continuous predictive models such as area under the receiver (AUC), sensitivity, specificity, predictive accuracies, and so on do not necessarily translate into bottom line effect in clinical practice. For example, heart rate characteristics monitoring for neonatal sepsis has a modest AUC and yet allowed more than 20% relative reduction in mortality in a large randomized controlled trial (12). And, of course, it also may be true that a test with high AUC may result in no useful effect on clinical practice.

The optimism of forward-thinkers like Eric Topol (@EricTopol) is contagious, justifiably so. For sure, clinical decision support from computerized algorithms will more and more be a part of our daily practice. Just as a certain generation of clinical cardiologists looks back in awe at how technology has improved our practice in the past 30 years, future healthcare providers may wonder how one ever made do without modern decision support tools .

But it still comes down to standing next to one patient at a time today, and the sinking feeling that you are missing something. Let's look forward to apps for that, ones that were made the right way.

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Is A Diagnosis of Sepsis Sufficient to Warrant Stress Ulcer Prophylaxis?*

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***See also p. e464.**

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The use of stress ulcer prophylaxis is common in the ICU. Although it is commonly accepted that a subset of critically ill patients is at risk for stress-related mucosal damage (1), the prevalence of clinically important bleeding in the ICU is quite low (1–4). Well-established indications for stress ulcer prophylaxis in the ICU include mechanical ventilation for at least 2 days and coagulopathy (5). Other risk factors that have been implicated as being potentially associated with clinically important bleeding include sepsis, ICU stay longer than 1 week, occult bleeding lasting longer than 6 days, use of high-dose corticosteroids, and history of gastrointestinal bleeding or ulceration within the previous year (2).

The evidence for routine use of stress ulcer prophylaxis for patients who are not ventilated or coagulopathic is mixed, at best, and is limited by a lack of high-quality studies. The Surviving Sepsis Guidelines recommend the use of stress ulcer prophylaxis for patients with severe sepsis or septic shock who have risk factors for bleeding (defined as "coagulopathy, mechanical ventilation for 48 hours, possibly hypotension") but also suggests that patients without risk factors not receive prophylaxis (6).