Crystal Balls and Magic Eight Balls: The Art of Developing and Implementing Automated Algorithms in Acute Care Pediatrics*

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It has taken years of arm-twisting, but we finally find ourselves immersed in the era of digital healthcare with widespread implementation of electronic health records (EHRs). Clinicians and researchers are increasingly interested in leveraging this digital infrastructure to improve patient care (1). Automated algorithms for early detection or prediction of events are a natural fit for this new digital era but understanding how to build these successful data-driven systems is challenging. How do we turn away from the magic eight balls of algorithms that perform no better than a guess and find the true predictive crystal balls we need to improve patient outcomes? We suggest that we need accurate algorithms, effective clinical decision support (CDS), and continuous monitoring and improvement of these system to build the crystal balls of the future (**Fig. 1**).

ACCURATE ALGORITHMS

In this issue of *Pediatric Critical Care Medicine*, Eisenberg et al (2) present the performance of a continuous, automated EHR-based screening tool for the early detection of severe sepsis in a children's hospital. The authors make a laudable effort to tackle a tough clinical problem, but their study illustrates many of the challenges of automated algorithm development to predict rare nonspecific events. These issues exist both for algorithms based on expert opinion and prior knowledge (like the one presented by Eisenberg et al [2]) and those developed using clinical prediction modeling and other data-driven approaches.

One major challenge in building effective algorithms is predicting poorly defined events of interest. This challenge is exacerbated by the rarity of events like severe sepsis, which occurred in only 1% of patients in the study by Eisenberg et al (2). Detection is additionally difficult because sepsis occurs in many different locations throughout in the hospital as well as in heterogeneous patient populations with different risk factors. As a consequence, and despite our best efforts, the performance of algorithms designed to predict or detect these rare and poorly defined events may be poor resulting in a high number needed to alert (NNA), which is the number of patients in which an alert needs to go off before a "true positive" is detected.

Another fundamental challenge is achieving a desirable balance of true and false positives. Infrequent clinical events in acute care pediatrics could benefit from prediction or early warning tools. The consequences of missed cases or delayed care may be dire, so the potential gain from prediction or early detection is significant. This benefit, however, needs to be balanced with the rate of false alerts that are a natural consequence of poorly calibrated algorithms. Ideally, we would want a test that has both a high sensitivity and a high positive predictive value (PPV), but that is often impossible. Finding optimal balance is therefore key. The NNA, which is 1/PPV, may be helpful to put things in context. Different cutoffs of NNA may be helpful to determine the type of alert workflows and interventions that can be implemented around a triggering algorithm (**Table 1**).

EFFECTIVE CLINICAL DECISION SUPPORT

Using these improved algorithms as a baseline, the implementation of data-driven tools should occur in the setting of effective CDS systems. A CDS system is defined as "any electronic system designed to aid directly in clinical decision-making, in which characteristics of individual patients are used to generate patient-specific assessments or recommendations that are then presented to clinicians for consideration." (4) CDS systems have been shown to improve healthcare quality and safety (5–7), and there are evidence-based CDS recommendations that are pertinent for the implementation of prediction algorithms.

First, the speed of an information system is often the parameter that users value the most (8). The system must be reliable without interruptions or significant downtimes. Second, the system must meet the needs of the user. Optimal CDS systems anticipate latent needs and present data and information

*See also p. e516.

Key Words: clinical decision support systems; clinical deterioration; pediatric intensive care units; sepsis

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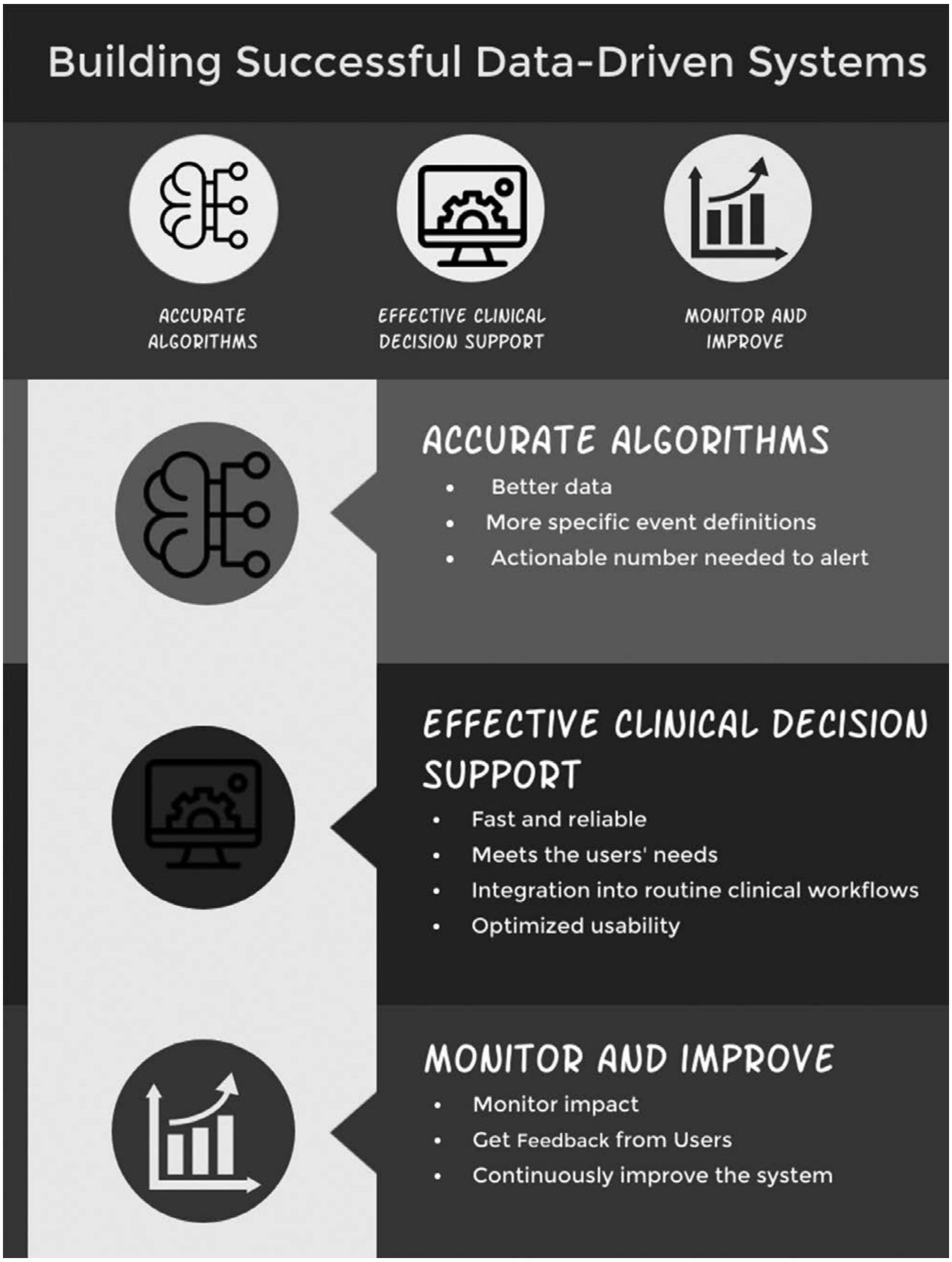

Figure 1. Overview of key components of successful data-driven systems.

at the time of decision (3). Next, to have success with alerts and algorithms, the CDS must be integrated into current practice, fitting seamlessly into a provider's clinical workflow. For early warning algorithms, the alerts should be coupled with CDS that incorporates human evaluation to confirm or deny the accuracy of the alert and assist in determining next steps. Recommendations for CDS within the acute care setting specifically focus on developing a system that allows for patient data review and the ability to prioritize multiple patients (9). Last, it must be easy for clinicians to do the "right thing" at the "right time," (10) thereby creating systems that are highly usable.

MONITOR AND IMPROVE

In addition to improved algorithms and effective CDS, a successful data-driven system needs ongoing evaluation and feedback. Monitoring, evaluating, and continuously improving decision support interventions after they are deployed is vital to the success of CDS (11). A standard process for reviewing override rates, complaints, and updating information based on current guidelines and evidence must be in place and supported for CDS to be successful. Feedback buttons and areas for comments are one step, but feedback to clinicians also must be available to demonstrate how comments are being used to improve the system. In addition, monitoring of performance of the algorithm over time is important as changes in documentation and other workflows can impact the algorithm accuracy.

Although there are many challenges to building successful data-driven tools and creating true learning healthcare systems (12), we have outlined the essential components. However, we still must establish an infrastructure in organizations that supports this work. A successful data-driven organization needs to support informatics trained pediatric critical care physicians and other acute care providers who can understand the algorithm development and work side-by-side with data scientists and CDS developers. These data-driven tools must reside in a system of ongoing improvement, harnessing the continuously learning model. Effective data-driven systems are within our grasp, but they require improved algorithms, effective CDS, and ongoing improvement within a learning health system to succeed. Let us send the magic eight ball back to the kids' playrooms and work on developing the data-driven crystal balls we need.

TABLE 1. Examples of Alert Workflows and Interventions to Consider Depending on the Number Needed to Alert (1/Positive Predictive Value) at an Acceptable Sensitivity in Infrequent Clinical Events

NNA at an Acceptable Sensitivity	Examples of Alert Workflows and Interventions to Consider at the Different NNA Performance Levels
< 5	Tier 1
	Confirmatory testing, if available
	Escalation to higher level of care, if needed
	Early therapeutic intervention if warranted
5 to 10	Tier 2
	Bedside evaluation and escalation to tier 1 if needed
	Training centered around individual at-risk patients
	Just-in-time team-based simulations
> 10	Tier 3
	Increased team situational awareness through structured communication tools (3), standardized handoffs, and huddles
	More frequent assessments and escalation to tier 1 or 2 as needed

NNA = number needed to alert.

The NNA cutoffs, sensitivity level, and interventions used here are only illustrative and will change based on the clinical problem and resources available.

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