Predictive analytics, clinical decision support, and the future of sepsis treatment

Use data to make predictions, recommend interventions, and improve outcomes.

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Every year, over a million Americans are diagnosed with severe sepsis, and 15% to 30% of them die. Sepsis is considered the most expensive condition treated in U.S. acute-care facilities, costing nearly $24 billion in 2013.

Early recognition of sepsis symptoms followed by prompt intervention with antimicrobial therapy, aggressive fluid resuscitation, and frequent perfusion status monitoring are the keys to saving lives. Despite this knowledge, healthcare organizations struggle to promptly identify and consistently treat the condition. One challenge in developing a sound sepsis algorithm is that many factors influence whether a patient becomes septic, and early signs and symptoms may be nonspecific. Manually monitoring patient medical records to screen for sepsis is labor intensive and inefficient, and care providers' varying levels of

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awareness and experience make consistent care challenging. However, the Centers for Medicare and Medicaid Services (CMS) have established standards for sepsis care, which if not followed could result in payment reductions. Technology coupled with data analysis can help clinicians identify and respond to sepsis.

Types of analytics

The amount of patient data collected and available in healthcare is staggering, and 95% of U.S. hospitals use certified electronic health records (EHRs) to handle it. Typically, healthcare organizations use descriptive analytics to address data retrospectively and review events after they occur. This analysis helps organizations and clinicians learn from the past, but it limits their ability to act on real-time data as it's entered into the EHR.

Predictive analytics, on the other hand, allows organizations to analyze large amounts of historical data to forecast future patient events or behaviors. Using predictive analytics across thousands of patient sepsis records could yield useful information for identifying key triggers that contribute to sepsis development. This information can be used to build a model that can be applied, tested, and refined as a predictive tool in identifying at-risk patients.

To analyze data this way, you must know the target population, how much data will be needed to drive valid and reliable findings, and what modifications may be needed in the EHR to capture necessary data. For example, will any documentation need to be changed to capture important patient information and will any incomplete data entry need to be eliminated or accounted for in the analysis? Working with modeling experts, statisticians, and technical resources will help define the predictive analytics process.

The true power for impacting patient outcomes comes with prescriptive analytics, which provide clinicians with actionable items. The developed predictive model is embedded into a clinician's workflow, triggering an alert or prompt indicating what the system has found and suggesting evidence-based interventions to change the course of patient care. (See *Past, future, present.*)

Past, future, present

Data can be used to learn from the past, predict the future, and take action now.

Descriptive analytics address data retrospectively so organizations and clinicians can learn from the past.

Predictive analytics allow organizations to analyze large amounts of historical data to forecast future patient events or behaviors.

Prescriptive analytics use the predictive analytics model to create alerts and recommend evidence-based interventions.

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Clinical decision support

All analytics tie into the clinical decision support, which according to the CMS includes "computerized alerts and reminders for providers and patients, clinical guidelines, condition-specific order sets, focused patient data reports and summaries, documentation templates, diagnostic support, and contextually relevant reference information." Sepsis clinical decision support, for example, can involve continuously analyzing patient records using a developed predictive model for at-risk patients and then prompting clinicians for a response when criteria are met. The response could be an evidence-based sepsis order set or protocol or activation of a sepsis review team. Organizational stakeholders should review and discuss what appropriate system responses should be.

Effective clinical decision support is a multistep process. It should convey necessary information to the correct people through applicable channels in the appropriate intervention formats at the appropriate point in the clinician workflow. A well-developed sepsis model would continually scan multiple values (temperature, pulse, respiratory rate, pertinent lab values, medication orders, and comorbidities) in a patient's EHR and prompt the clinician when evidence exists for potential sepsis. The clinician would then follow the organization's evidence-based sepsis prevention protocol. Effectively applied clinical decision support can reduce errors and improve care quality and outcomes. Downstream effects include reduced costs and increased patient satisfaction.

Challenges

A systematic review of automated sepsis detection using EHR data shows that alerts don't necessarily lead to earlier interventions, and that earlier interventions don't consistently translate to improved outcomes. This performance variability highlights the need for additional research.

Some of the variability in results can be attributed to the need for sepsis detection algorithm refinement. Predictive models depend on data quality, and some or all structured data is manually entered, contributing to errors and bias.

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What nurses want

A study by Long and colleagues found that nurses have alert preferences. They prefer:

- alerts that are based on established treatment protocols initiated from the patient's condition rather than regulatory guidelines
- role-specific pop-up alerts that are worded to draw attention to urgent situations
- intervention recommendations provided at the time they're needed, such as notifying the provider, ordering diagnostic or therapeutic interventions, or initiating a sepsis protocol or alert response team.

Collected data must be analyzed to ensure that it's correctly triggering sepsis alerts. If the model being used is inaccurate, either triggering too many alerts or not enough, clinicians may stop trusting the alerts and disregard them.

Algorithms

In Manaktala and Claypool's 2017 study, a team defined and redefined the patient algorithm and rules built into the clinical decision support system. Unique to this study was the adjustment of the algorithm with several rules tailored to the prevalence of comorbid medical conditions that frequently mimic sepsis symptoms. Nursing documentation also was adjusted before data collection to clarify data-entry elements, and the algorithms were reviewed with subject-matter experts. The study provided real-time alerts to clinicians' mobile devices and introduced 3- and 6-hour evidence-based sepsis bundle order sets. In this study, a highly sensitive and specific decision support system that alerts nurses of high-risk sepsis patients paired with change management and clinician education reduced sepsis mortality by 53%.

Alert fatigue

Alerts enable early detection and intervention, but false positives can lead to alert fatigue. They disrupt clinical care and can desensitize clinicians to future alerts. False positives also introduce extra cost if interventions are provided based on nonspecific alerts. Sepsis prevention teams should identify what type of alert information is critical and helpful. (See *What nurses want.*)

Privacy

Patient privacy and confidentiality must be baked into data collection, analysis, and clinical decision support. Patients must have a sense of control over their personal health information. Any time data is collected, stored, transmitted, or disseminated, precautions should be taken to protect against privacy violations. One common way to achieve this is by stripping collected or analyzed data of personal identifying characteristics (names, medical record numbers, social security numbers, addresses, etc.) that are considered protected health information. If this information is required, the processes may need to be reviewed by an institutional review board to determine if patient consent forms should include electronic data searches and analysis.

Tool for saving lives

Developing and improving data analysis and clinical decision support requires clinician involvement. Nurses should be represented on teams that are implementing clinical decision support, and they should provide predictive analytic model feedback, review how decision support is built, use the clinical decision support in technology pilots, be involved in the evaluation and refinement stages, and help train and support staff on the new technology.

Surveillance using predictive analytics and clinical decision support in the EHR can speed sepsis detection and promote early intervention. More research is needed to help build a robust knowledge base around clinical decision support related to sepsis. As additional organizations adopt sepsis alerts and protocols, we will begin to understand more about how new technology can enhance practice and save lives. ★

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