HARNESSING THE POWER OF ELECTRONIC MEDICAL RECORDS: *USING SEPSIS AS A CASE EXEMPLAR*

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Objectives

1. Differentiate clinical alerts, decision-support and machine learning within the context of a clinical problem addressed by technology within patients' electronic health records (EHR).
2. Describe how clinical support for best practices need to evolve with changes in evidence-based knowledge.
3. Outline how a clinician can contribute to the design, testing, implementation and evaluation of clinical decision support applications.

Historical Perspectives Sepsis Best Practice

- Recognized International problem 1990s
- First best practice recommendations 2004
- Revisions 2008, 2013, 2016, 2018
- Studies show attempts to follow best practice can reduce mortality
- Every hour delay in appropriate treatment increases mortality 7.6%
- More than half US hospital deaths attributable to sepsis and 6.2% of all hospital costs

Sources: Cecconi et al, 2018; Center for Medicare Services, 2021; Levy et al, 2018; Rhodes et al, 2016

Why is an EHR solution with a Sepsis Program Important?

- Having an EHR solution with a sepsis program gives hospitals and health networks a leg up on identifying and managing at-risk patients.
- Any system that saves time and takes out the guesswork for providers is worth the investment.
- The problem of sepsis is so big, that return on investment is huge.

Using any standardized and structured process results in better patient outcomes. Compliance <30% can still decrease mortality 3-6% and compliance > 52% can reduce mortality 20%

Sources: Burdick et al, 2020; Byuk et al, 2021; Giacobbe et al, 2021; Hassan et al, 2021; Kausch et al, 2021; Levy et al 2014; Ruppel & Liu, 2019

Artificial Intelligence in Healthcare

- Definitions
  - IT systems that sense, comprehend, act, and learn.
  - Intelligence demonstrated by the ability to depict or mimic human brain functions
  - Should it really be termed augmented intelligence because it helps humans work better?
  - Data science supported by clinicians vs clinical science supported by data?
- Common applications
  - Pattern recognition of images (e.g. retinal photography, radiologic images, cervical visualization and correlation to pathology)
  - Clinician prompts
  - Tracking tools
- Screening and diagnostic descriptions, not prescriptive

Sources: Deo et al, 2016; Miotto et al, 2018; Secinaro et al, 2021; Singh et al, 2020; Yu et al, 2018

Machine Learning in Clinical Practice

Low level prompts

Best practice alerts appear when the clinician enters a field deemed to have recommended interventions. Advice prompts exist with specific fields.

Reminders

The system knows what should be done when and provides reminders to clinicians when they log-in, but can be ignored, silenced, or dismissed.

Templated requirements

Templated entries require a specific response and will not allow signature or sign-out until performed as expected or explanation provided.

Interactive technology

The program recognizes electronic record triggers, provides templated prompts requiring response, reminders, and learns from answers to modify future prompts.

Sources: Deo et al, 2016; Miotto et al, 2018; Secinaro et al, 2021; Singh et al, 2020; Yu et al, 2018

Integrated EHR Identification and Management Solutions in Sepsis

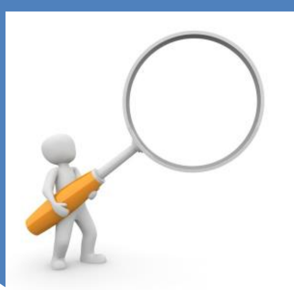
- The Facts…. Most clinicians
  - prefer to rely on an EHR vendor for sepsis technology
  - want sensitivity and specificity so their time is not wasted
  - desire use of real-time data and immediate notification
  - expect the system to expedite care between clinicians
  - want to see return on investment with improved patient outcomes

- The Features
  - Quality and surveillance
  - Communication
  - Visibility of essential information
  - Watchlist capability
  - Expert-based content
  - Customizable
  - Education about use and application

Sources: Burdick et al, 2020;Harrison et al, 2016; Hassan et al, 2021; Ruppel & Liu, 2019; Wu et al, 2021

Components of Current EHR Sepsis Management Systems

Identification



Notification

Evaluation

Clinical action

Reporting and Analytics

Continual tracking of all patients to detect sepsis early

Sources: Burdick et al, 2020; Giacobbe et al, 2021; Harrison et al, 2016; Kausch et al, 2021; Ruppel & Liu, 2019; Wong et al, 2021; Wu et al, 2021

Elements that Must be Extracted to Achieve Goals

- Case finding
  - Microbiology data
  - ICD-10 codes
  - CPT codes
  - Patient outcomes
- Predictive of risk
  - Demographics/PMH/PSH/ morbidities
  - Inflammatory/ specialty biomarkers
- Diagnostics
  - Laboratory
  - Imaging
- Management
  - Order system
  - Medication administration records
  - Intake/ output records
  - Clinical notes
- Analytics
  - Data integration
  - Ability to detect key words in clinical notes
  - Dashboards
  - Outside or scanned data integration

Sources: CDC, 2021; Giacobbe et al, 2021; Hassan et al, 2021; Wong et al, 2021

Facilitators in Operationalizing Sepsis Alert Systems

Motivation

- Magnitude of the health problem
- Presence of known best practices
- Proven outcome benefits
- Government prioritization
- Potential cost savings

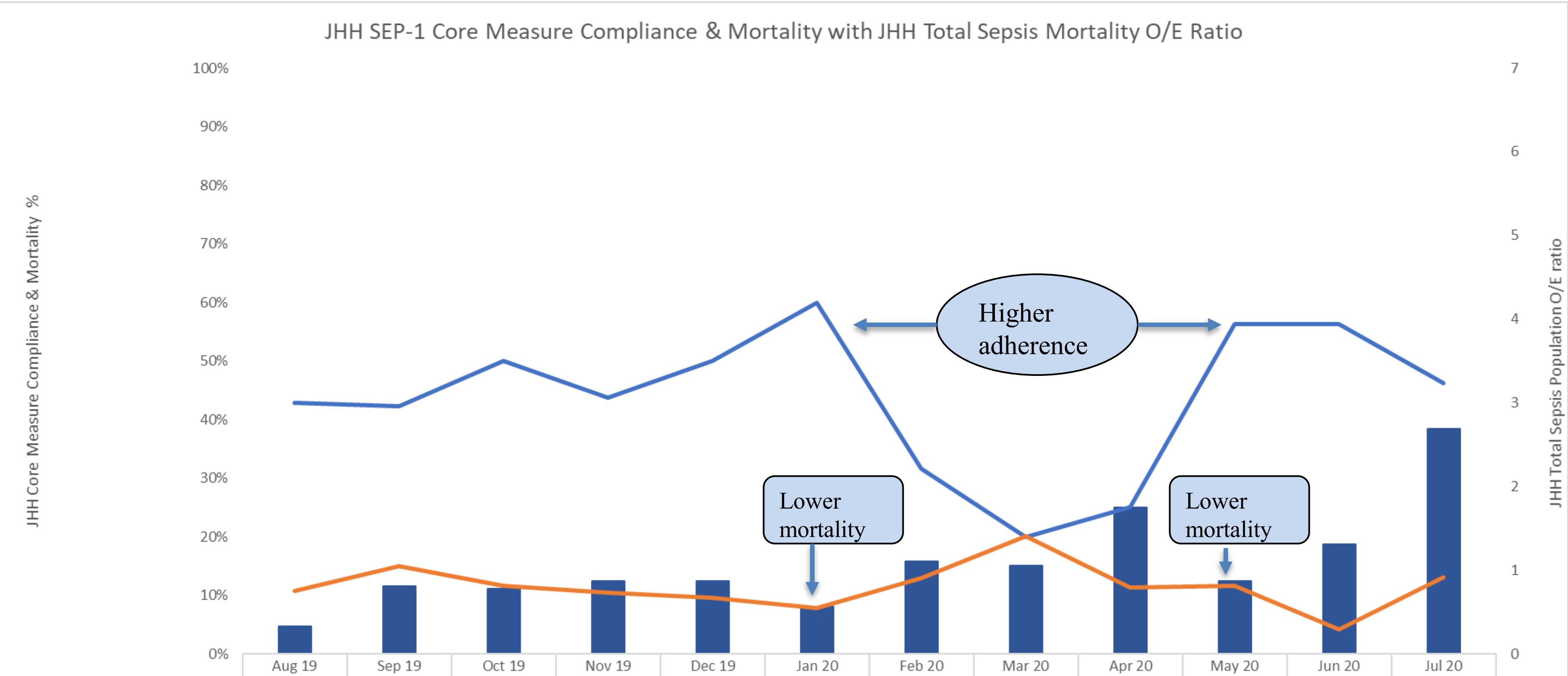
Resources

- Ready access to phlebotomy
- Efficient Infectious disease workflows
- Pharmacy/ medication access
- Prompt provider responses

Sources: Burdick et al, 2020; Giacobbe et al, 2021; Ruppel & Liu, 2019; Wu et al, 2021

Johns Hopkins East Baltimore Sepsis Core Measure

SEP-1 Compliance and O:E Mortality



	Aug 19	Sep 19	Oct 19	Nov 19	Dec 19	Jan 20	Feb 20	Mar 20	Apr 20	May 20	Jun 20	Jul 20
JHH SEP-1 Mortality	5%	12%	11%	13%	13%	8%	16%	15%	25%	13%	19%	38%
JHH SEP-1 Compliance	43%	42%	50%	44%	50%	60%	32%	20%	25%	56%	56%	46%
JHH Sepsis Mortality O/E	0.76	1.04	0.81	0.73	0.67	0.55	0.90	1.41	0.79	0.82	0.29	0.92

Updated 6/7/2020

Operational Challenges in Sepsis Alerts

The Science

- Frequent changes in knowledge and adjustments in best practice recommendations
- Sepsis presentation and management associated with unique variables can defy predictability in severity of illness
- Certain populations have known contraindications for specific interventions but actions may not yet be customizable enough
  - Cancer/ immunocompromised
  - Immediate post-operative
  - Heart failure
  - Renal failure
- Currently four new biomarkers of sepsis presence or severity in clinical trials, which may affect model performance unless rebuilt

Sources: Center for Medicare Services, 2021; Su et al, 2021; Taneja et al, 2021; Wu et al, 2021

Operational Challenges in Sepsis Alerts

Organizational

- Most sepsis predictive systems target bacteremia in clinical findings and diagnostic testing
  - Other infections may be missed
  - Limited diagnostic options may require staff go to multiple places for cues to provide complete care
- System-wide implementation requires standardization that may not be as sensitive or specific for certain populations
- Heavily dependent upon current objective data that do not reveal accurate diagnosis 62% of the time
- Not all systems are created equal

Sources: Javan & Sepehri, 2021; Kausch et al 2021; Ruppel & Liu, 2019; Singh et al, 2020; Wu et al, 2021

Operational Challenges in Sepsis Alerts

Personnel performance

- Success may depend upon organization resources
- Commitment to use the tools needed to ensure optimal machine learning of patterns
- Education intensity and repeated experience required to master and understand capabilities

Sources: Asan et al, 2020; Pettigand et al, 2020; Ruppel & Liu, 2019; Singh et al, 2020; Wu et al, 2021

Limitations of EHR Sepsis Best Practice Programs

- Finite options don't address all decisions
- Systems not able to differentiate ending of one infection or start of another, so often only used for first event
- Alert fatigue by clinicians
- Does not handle exceptions well
- Can't replace clinical reasoning

Sources: Giacobbe et al, 2021; Javan & Sepehri, 2021; Singh et al, 2020; Wong et al, 2021; Wu et al, 2021

Bundle Element Recommendations:

Levels of Evidence

Recommended practice	Recommendation	Quality of Evidence
Lactate collected within 3 hr	Weak	Low
Blood cultures collected within 3 hr and before antibiotics	Best practice statement	--
Appropriate antibiotics given within 3 hr	Strong	High/ Moderate
IV fluids given within 3 hr at correct amount and rate	Strong	Low
Repeat lactate drawn after IV fluids and within 6 hr	Weak	Low
Persistent hypotension documented after IV fluids	No statement	--
Focused physical exam performed after IV fluids and within 6 hr	No statement	--
Vasopressors started within 6 hr, Norepinephrine vasopressor of choice	Strong	High/ moderate

Sources: Byuk et al, 2021; Center for Medicare Services, 2021; Coopersmith et al, 2018; Levey et al, 2014; Levy et al 2018, Rhodes at el, 2016

Changes in Clinical Practice

	SEP-1	SEP-3
Definitions	Sepsis, Severe sepsis, septic shock	Sepsis, septic shock
Screening tools	SIRS criteria	qSOFA
Diagnostics	Lactate, Blood cultures	Obtain within 1 hr
Management	Structured antibiotic choices Antibiotics within 3 hr Liberal fluids lactate > 2.0	Flexibility in antibiotic choices when cause known Antibiotics within 1 hr Conservative fluids Lactate > 4.0 Additional option to add vasopressin Corticosteroids only if vasopressors required
Timeframes	3, 6, and 24 hour timeframes	1, 3, 6, and 24 hour timeframes

Sources: Byuk et al, 2021; Cecconi et al, 2018; Levy et al 2018; Osborn, 2017

Available Resources for Developing EHR-based Sepsis Alerts

- Agency for Healthcare Research and Quality (AHRQ) Enhancing an EMR-Based Real-Time Sepsis Alert System Performance Through Machine Learning (Michigan) | AHRQ Digital Healthcare Research: Informing Improvement in Care Quality, Safety, and Efficiency
- Centers for Disease Control and Prevention (CDC) https://www.cdc.gov/sepsis/pdfs/Sepsis-Surveillance-Toolkit-Mar-2018_508.pdf
- Center for Medicare Services Sepsis Core Measure: : https://cmit.cms.gov/CMIT_public/ViewMeasure?MeasureId=1017
- Surviving Sepsis Campaign https://www.sccm.org/SurvivingSepsisCampaign/Guidelines
- Sepsis Alliance https://www.sepsis.org/
- The Joint Commission https://www.jointcommission.org/resources/patient-safety-topics/infection-prevention-and-control/sepsis/
- Society Critical Care Medicine https://www.cdc.gov/sepsis/pdfs/Sepsis-Surveillance-Toolkit-Mar-2018_508.pdf

New Developments in Sepsis Prediction

- Novel biomarkers
- Machine learning systems improve predictability over time
- Methods to balance outcomes- enhanced sensitivity and specificity and predictive timeframe are usually inversely related

Sources: Hassan et al, 2021; Su et al, 2021; Taneja et al, 2021

Sepsis Alert Systems

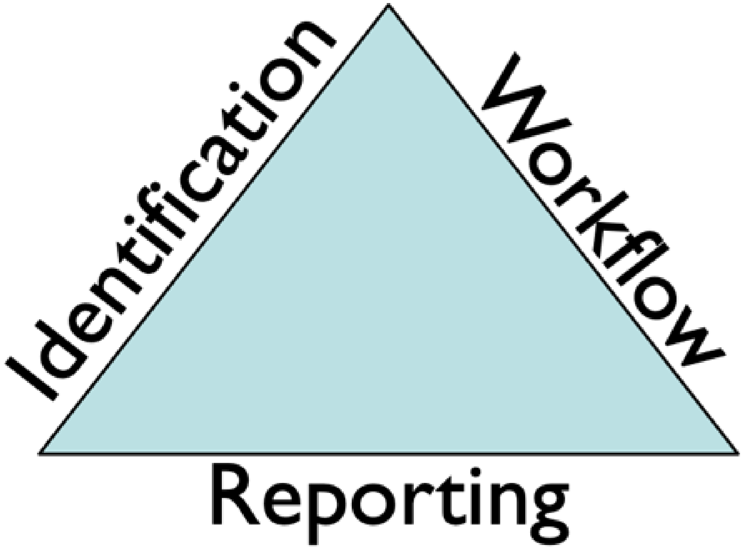
All have specificity in approx. 66% range

At least 14 different models identified in 2021 integrative reviews; 3 others found in google search

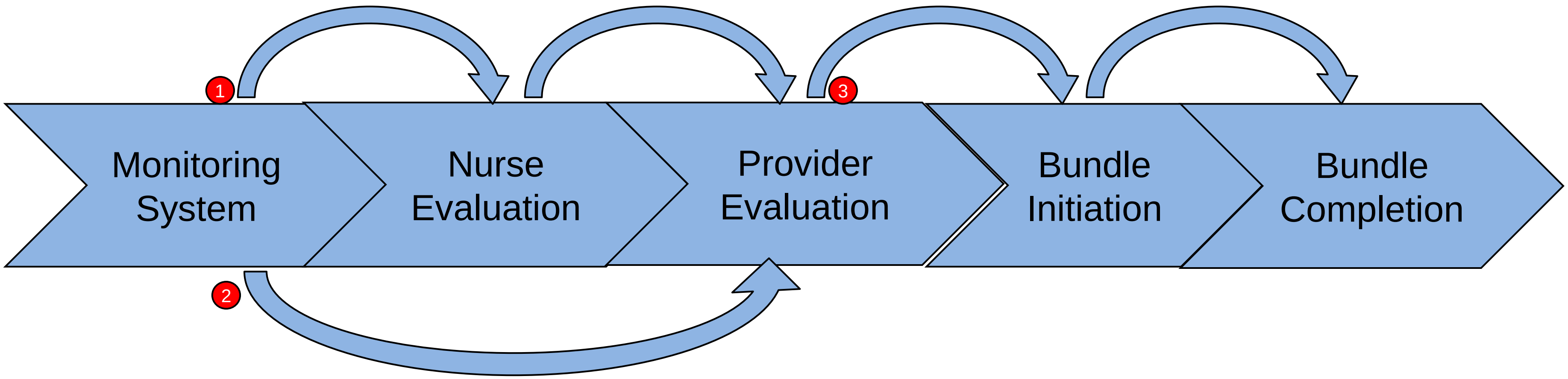
Sepsis Identification through Merged Clinical and Electronic Health Data

Analysis Strategy

- Identification—how well does the algorithm **identify patients at risk** for sepsis?
- Workflow—how well is **sepsis bundle completion** supported?
- Reporting—can we produce the **reports** needed for quality initiatives?



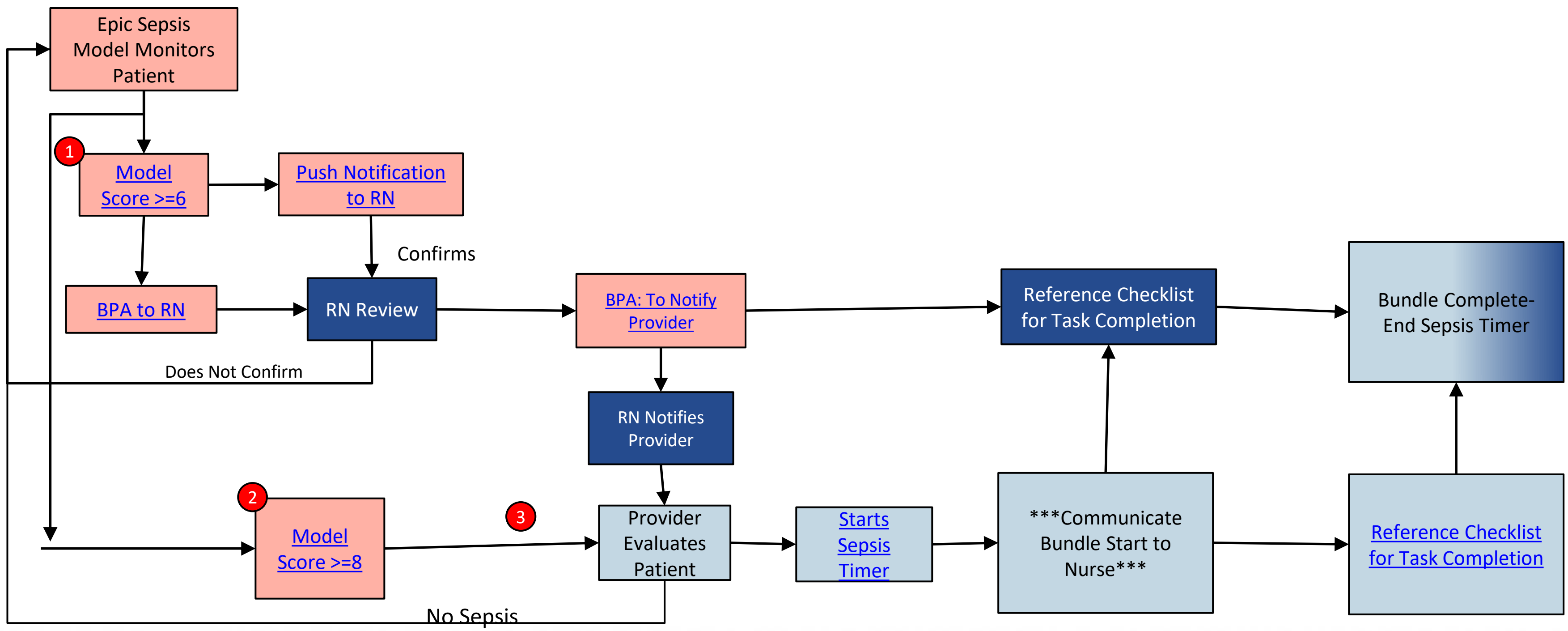
High Level Overview



Workflow Diagram

3 Entry Points into Workflow:

1. Epic BPA/Push Notification Alerts RN
2. Epic BPA Notifies MD
3. Provider Initiates based on clinical judgement with/without RN Communication



Source: "EPIC Sepsis Model", EPIC Electronic Health Record

Nurse | Provider | Epic

EPIC Sepsis Workflow

EPIC BPA

- BPA alert in Epic Hypserspace or Rover Push Notification for bedside nurse.
- Nurse completes 3 Screening Questions
- If prompted, **notify provider immediately** and document Provider Notification: "Concern for Sepsis"-This can be completed within the BPA

Provider Decision

- Upon notification by nursing, open Epic and "Start Sepsis Timer", place orders using sepsis order set if sepsis is suspected, snooze if data is pending, or dismiss by clicking "Continue Current Care".
- Note: You can track completion of sepsis bundle in the sepsis navigator.

Sepsis Orders

- Obtain STAT lactate and blood cultures; administer STAT antibiotics **within 30 min of order.**
- If unable to obtain cultures notify provider.
- Note: Antibiotics may have to be given first. Document unsuccessful attempts to draw blood cultures. Continue to attempt to get blood cultures after antibiotic administration.
- **Goal is to have these orders completed within 1 hour from start of sepsis timer.**

Cont. Sepsis Order

- For signs of hypoperfusion (hypotension, lactate ≥ 4.0), begin rapid infusion of 30 mL/kg crystalloid.
- Note: For obese (BMI > 30)patients, it is appropriate to dose crystalloid fluid by ideal body weight.
- In pregnancy, 20 mL/kg is recommended.
- Document any contraindications to rapid crystalloid infusion, e.g. severe CHF, ESRD, or severe anemia.

Cont. Sepsis Order Set

- Repeat lactate if initial lactate > 2 mmol/L.
- Initiate vasopressors if hypotensive after fluid resuscitation, to maintain a MAP ≥ 65 mmHg.
- Reassess and document perfusion.

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Variables Considered in JHH EPIC Sepsis Model

- Data elements
  - Demographics
  - Diagnoses (primary and comorbidities with increased risk for infection)
  - Lab results in past 72 hours
  - Medications (causing risk for infection, used to treat infection)
  - Lines, drains, airways
  - SIRS criteria (SEP-1)
- Weighting
  - Each provide different percentage contribution to score
  - Updated every 15 minutes
  - Some factors have less/ more importance when paired with the immediate observation findings of patient

Score Summary

BestPractice Advisory - Orders, Alabama

Critical (1)

Potential Sepsis Advisory

This patient meets Sepsis Predictive Model Criteria.

Complete the following sepsis screening questions.

Document | Do Not Document | Flowsheets Collapse

Sepsis Screening

Are rigors/severe shivering/chills present?

Yes No

Does the patient have new altered mental status?

Yes No

Does the patient have signs/symptoms of a new/worsening infection?

Yes No

Proceed to Sepsis Navigator for Data Review

Acknowledge Reason

Snooze 15 mins for clinical review | Not on Primary Team

Accept

BestPractice Advisory - Orders, Alabama

Critical (1)

Potential Sepsis Advisory

This patient meets Sepsis Predictive Model Criteria.

Please notify the appropriate provider about this patient's sepsis alert.

Document | Do Not Document | Flowsheets Collapse

Provider Notified

Reason for Communication

Change in status | Concern for Sepsis | Critical lab values

Critical Vitals Value Out... | Patient/ Caregiver request | Provider Evaluation

Other (Comment)

Name of Provider notified

Time Provider Notified

Proceed to Sepsis Navigator for Data Review

Acknowledge Reason

Snooze for Provider Notification | Not on Primary Team

Accept

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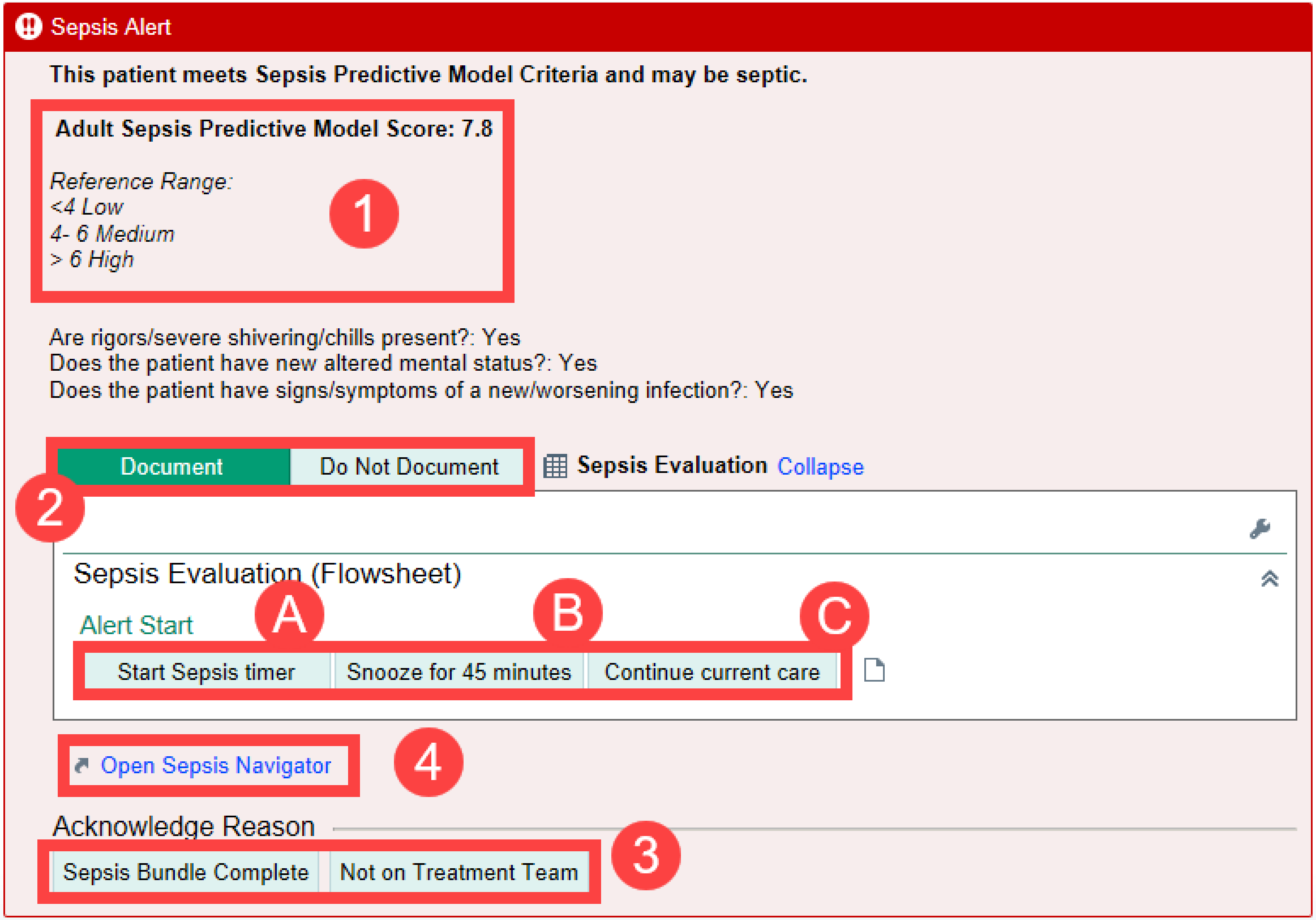
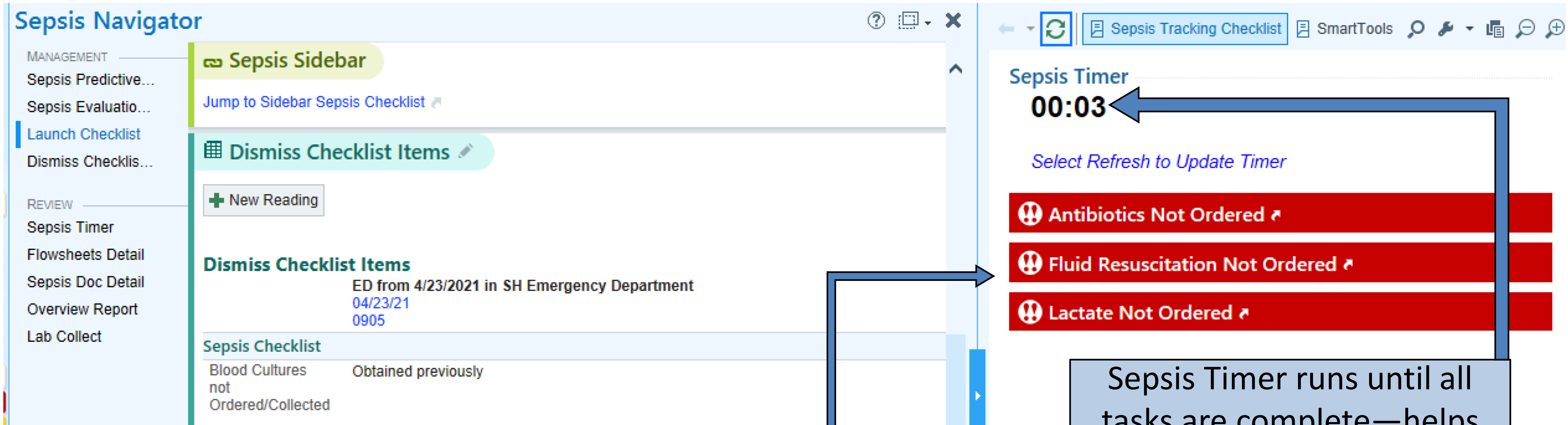

Sepsis Alert
This patient meets Sepsis Predictive Model Criteria and may be septic.
Adult Sepsis Predictive Model Score: 7.8
Reference Range:
<4 Low
4- 6 Medium
> 6 High
1
Are rigors/severe shivering/chills present?: Yes
Does the patient have new altered mental status?: Yes
Does the patient have signs/symptoms of a new/worsening infection?: Yes
Document
Do Not Document
2
Sepsis Evaluation
Collapse
Sepsis Evaluation (Flowsheet)
Alert Start
A
B
C
Start Sepsis timer
Snooze for 45 minutes
Continue current care
Open Sepsis Navigator
4
Acknowledge Reason
Sepsis Bundle Complete
Not on Treatment Team
3

Sidebar Checklist

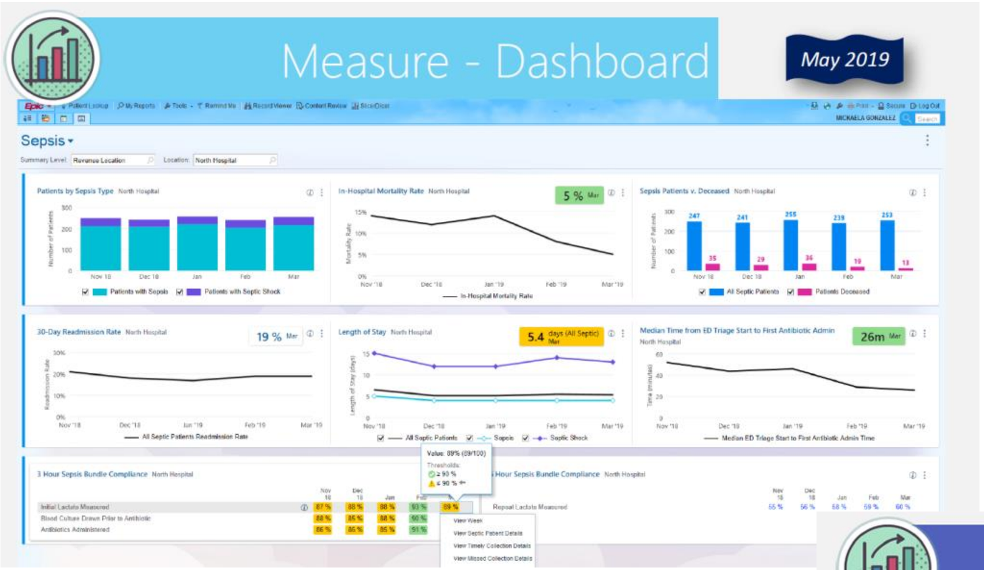


Dynamic List that shows only remaining elements of the required 3 & 6 Hour Bundle Components

Sepsis Timer runs until all tasks are complete—helps keep track of 3 & 6 hour bundle components

Return to Workflow Diagram

Epic: Measuring Sepsis Performance



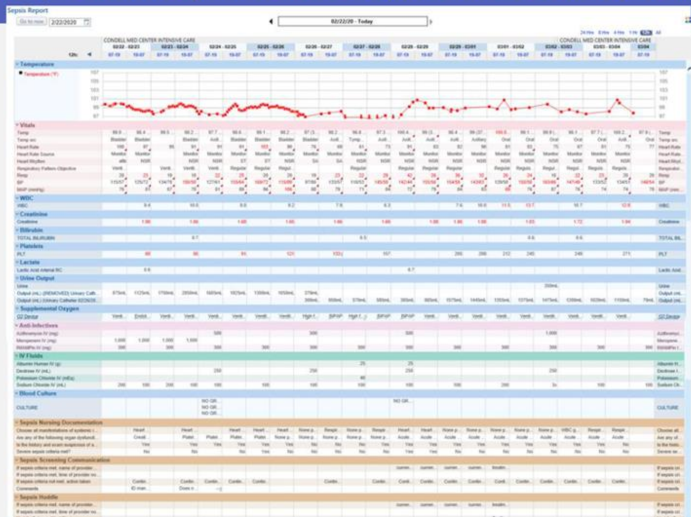
You can't improve something you don't measure it ……

Patient Summary Timeline Report for Chart Review

- Link for Reporting Workbench to view retrospective Timeline of Sepsis for patient
- Create an accordion report to connect vitals, labs, meds, screening questions, and sepsis score for retrospective or real-time analysis of a patient's sepsis course
- Primarily make available to administrative, informatics, management, and/or quality staff for reviewing workflow, timing, compliance

**accordion reports don't display well in Reporting Workbench, so you'll need to open the chart and review the patient.*

***Foundation Report – LRP 3041000215*




The End

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