Ontario Critical Care Clinical Practice Rounds (OC3PR): COVID-19

Nov 30 2022

Early Warning Systems... Now to the Future

Chaired by Dr. Dave Neilipovitz

Presented by Dr. Mike Miletin and Dr. Muhammad Mamdani

Meeting Etiquette

- Attendees can submit questions to Q&A in the Zoom icon in the menu
- Please note, reproduction in part or in full of any of this presentation requires express permission from CCSO.

Hosted by

CCSO | SMPCO

ccso.ca

Learning Objectives

Upon completion of this activity, the participants will be able to:

1. Understand the importance of timely recognition of the deteriorating patient and failure to rescue from a patient safety lens
2. Recognize the value of EWS in enhancing patient safety and optimizing the function of Critical Care Response Teams (CCRTs)
3. Be familiar with the various types of EWS currently in use; their evidence and critiques
4. Gain an appreciation of the future of EWS including machine learning/AI approaches

Recognition of the deteriorating patient

- About 20 – 30% of admissions to medical intensive care units are unplanned transfers from the ward
- These patients have double the mortality rate compared to patients admitted to the ICU from the ED or PACU, at about 30%

- 80% of ward patients requiring ICU transfer have 3 or more SIRS criteria within 24h of transfer
- Most of the other 20% have alterations in level of consciousness

CCRT: Critical Care RESCUE team

CCRT deployment has been associated with decreased code blues, decreased hospital mortality, and a lower acuity at ICU admission

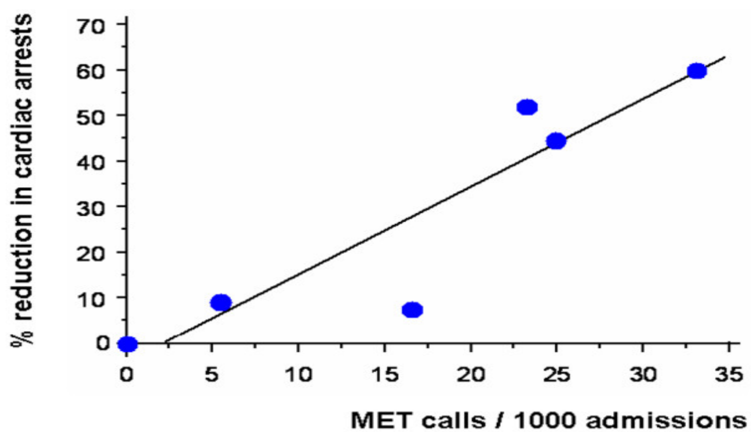
BioMed Central The Open Access Publisher | CRITICAL CARE

this article | search | submit a manuscript | register

PMC full text: Crit Care. 2009; 13(5): 313.
Published online 2009 Oct 6. doi: 10.1186/cc7996
Copyright/License ► Request permission to reuse

<< Prev Figure 1 Next >>

Figure 1



Scatter plot and line of regression showing association between increased Medical Emergency Team (MET) call rate ('MET dose') and percentage reduction in cardiac arrest rate from baseline. Adapted from Jones and colleagues [16].

Crit Care

Crit Care

MERIT: "The response team paradox"

- MERIT cluster randomized trial (Lancet 2005): negative
- Sensitivity of calling criteria used in MERIT to predict cardiac arrest, ICU transfer, and death was only 50%

  (Specificity 96%). <u>We use the same criteria</u>

- Part of the poor sensitivity was attributed to the lack of calls made despite criteria being present

- Bottom line: CCRTs were not activated as frequently as they were needed ie the "dose" was too low

Why do we underdose CCRT?

CCRT activation depends on:

- Diligence in measurement of vital signs
- Accuracy of measurement and observations
- Integration of the data into a judgement of patient’s condition (or a prediction of outcome)
- Action

How do we optimize RRT activation?

- Consider improving the performance of the signal or “afferent” arm

- Hard wire or use a “forcing function”

- That is the rationale for EWS in a nutshell

Early Warning

- Systematic (usually computer assisted) scrutiny of vital sign datasets, looking for abnormal patterns that are known to predict bad outcomes (ICU transfer, cardiorespiratory arrest, death)
- Abnormal patterns packaged as “alerts” and communicated (in real or near-time) to an accountable care provider
- Response is well-defined, scalable, patient focused

Intuition

- Experienced bedside clinicians (nurses and doctors) often have good intuition about which patients are “sick”

- Do we really need a computer to tell us who is sick?

- We may over-rely on our intuition (System 1), especially when fatigued, cognitively overloaded and moving fast

Challenges that ward staff face daily

- Higher volumes of complex, sick patients
- New technology and treatment regimes
- Increased novice to expert staff ratio

- Cognitive overload and multitasking

- Alarm fatigue

- Variable ward physician expertise and availability

Algorithms PLUS intuition

- Humans are not great at integrating lots of pieces of information into the big picture quickly AND accurately…we need to think it through (System 2), and that takes a lot of time

- We can ask an EMR to run a checklist or algorithm and tell us if our patient has SIRS (80% of ICU admissions from wards) or altered LOC (the other 20%)

- We can design an algorithm to be very sensitive (pick up everyone, but lots of false positives) or very specific (misses some, but the ones it picks up are “real”)

- Setting these characteristics is best determined by where we choose to assign accountability for the measurement and response to vital signs

Which Early Warning Score to choose? (there are > 20)

Literature has been mostly about which systems are best at discriminating between patients who have bad outcomes and those who don’t

Most regression-based systems perform similarly

(AUC 0.7 to 0.8)

What matters:

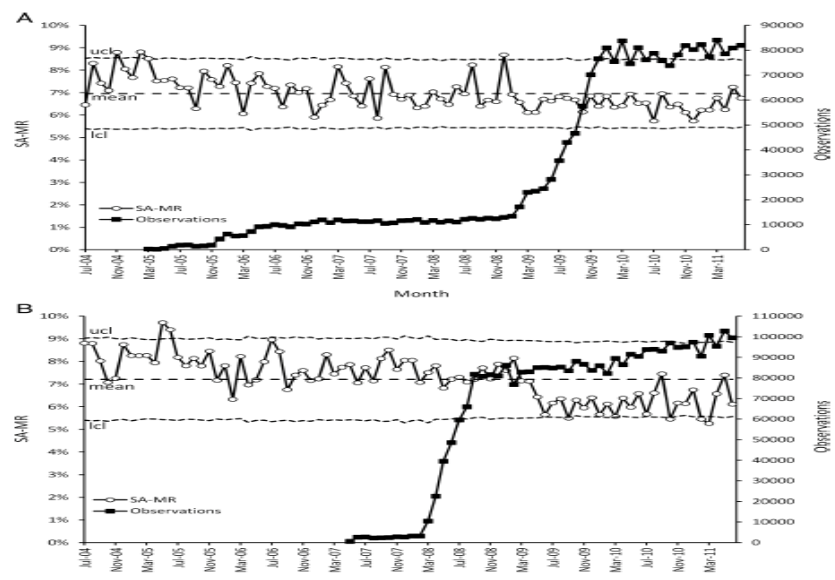
- properly matching the alert to the level of accountability
- reducing alarm fatigue

Outcome studies: Track and trigger systems – several vital signs, weighted by degree of abnormality into a composite

- Bellomo 2012: (18,000 patients, multicenter) Increased CCRT activation, improved survival if seen by CCRT
- Subbe 2017: (UK, 2000 patients) Decreased rate of severe sepsis, cardiac arrest, death
- Schmidt 2015: (UK)

  Decrease in

  hospital mortality



Early warning system development at a large community teaching hospital: AEGIS

Feedback loop:

- Vital signs taken by ward caregiver
- Vitals entered into/wirelessly sent to EMR
- Triggers: Abnormal vitals, CCRT calling criteria (simple cutoffs, no complex scoring system) and SIRS
- Alert sent to team leader’s mobile device

AEGIS

- First responders: Team leader and bedside RN
- Further response is scalable depending on degree of patient acuity
  - Review at am rounds/MRP call/CCRT call
  - Trigger for goals of care discussions

Alert Notification

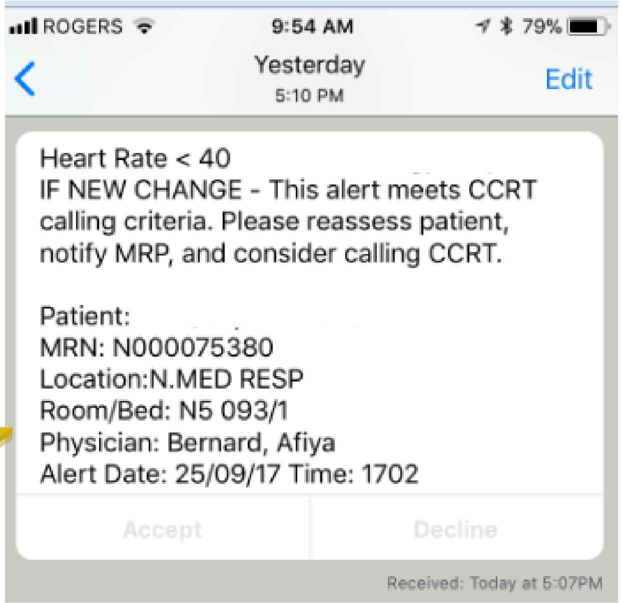

ROGERS 10:28 AM 57%
Yesterday
8:56 PM
Edit

Patient has met SIRS Criteria - HR>89 + Temp>37.8 or <36 + WBC>12 or <4
Please reassess patient. If New or Patient Condition worsening, notify MRP.

Patient:
MRN: N000650554
Location: N.MED RESP
Room/Bed: N5 049/1
Physician: Kapoor, Vikram
Alert Date: 11/10/17 Time: 2023

Accept | Decline

Received: Today at 8:44PM


ROGERS 9:54 AM 79%
Yesterday
5:10 PM
Edit

Heart Rate < 40
IF NEW CHANGE - This alert meets CCRT calling criteria. Please reassess patient, notify MRP, and consider calling CCRT.

Patient:
MRN: N000075380
Location:N.MED RESP
Room/Bed: N5 093/1
Physician: Bernard, Afiya
Alert Date: 25/09/17 Time: 1702

Accept | Decline

Received: Today at 5:07PM

AEGIS uses a decentralized system: No significant increase in workload

Number of new alerts = 3 per shift per ward of 30 patients

Total alerts: average 6 per shift per ward

In one month:

44 new alerts
5 patients – increased frequency of vitals
2 patients required CCRT consult
7 patients had new antibiotics ordered
7 patients had imaging ordered
5 had samples of blood or urine sent to microbiology
2 had fluid boluses ordered
1 patient had a goals of care conversation

Pilot Outcomes

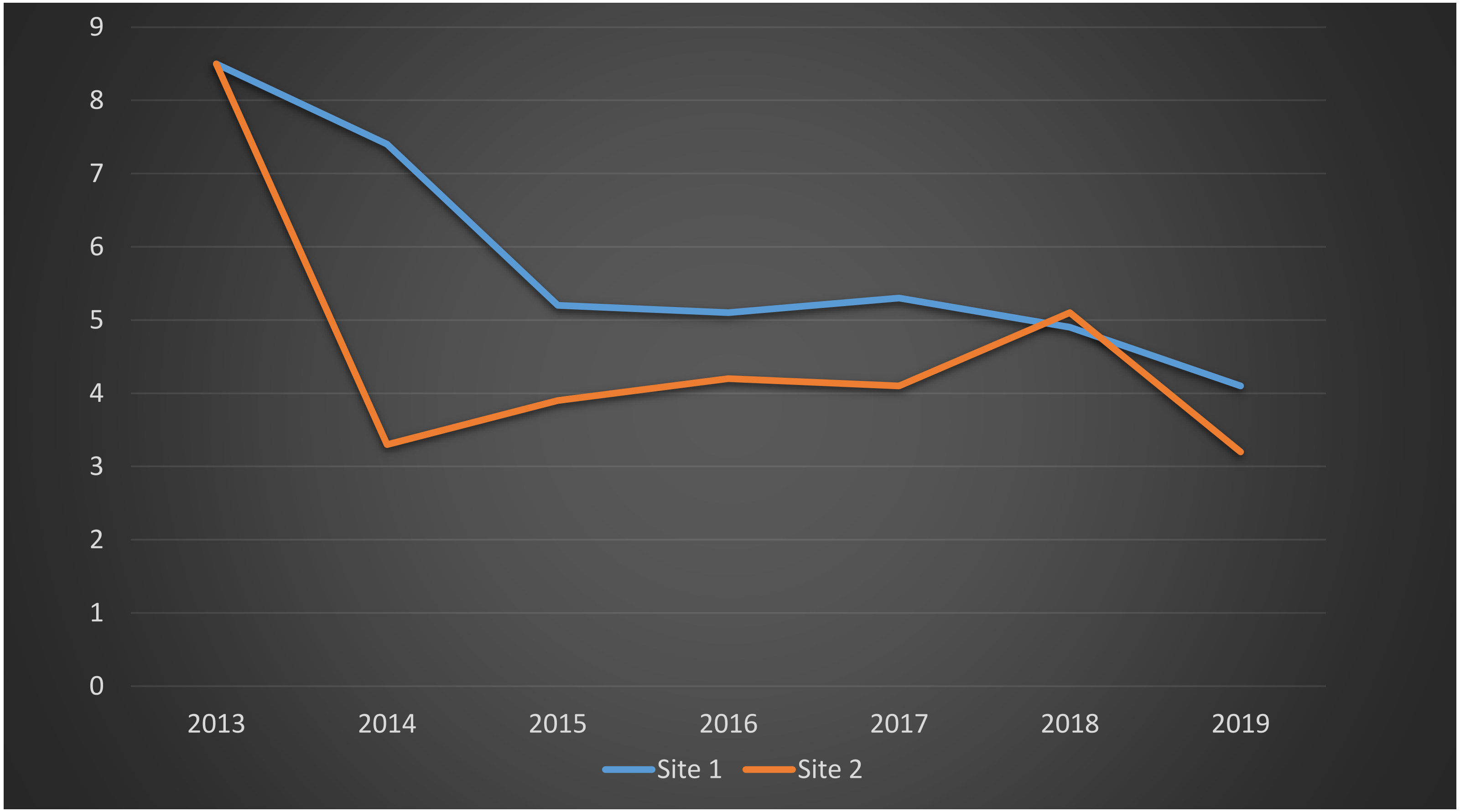
1 year results:

- 35% reduction in code blues
- 18% reduction in unplanned ICU admissions
- 2-4 lives saved each month

- Day/Night shift team lead situational awareness
- Nurse to MD communication – enhanced with a shared mental model “our patient just triggered an AEGIS alert”

- In 2015, AEGIS was expanded to the remainder of the medical and surgical inpatient units at Osler
- We now have access to ward specific rates of code blue, death, and ICU transfer

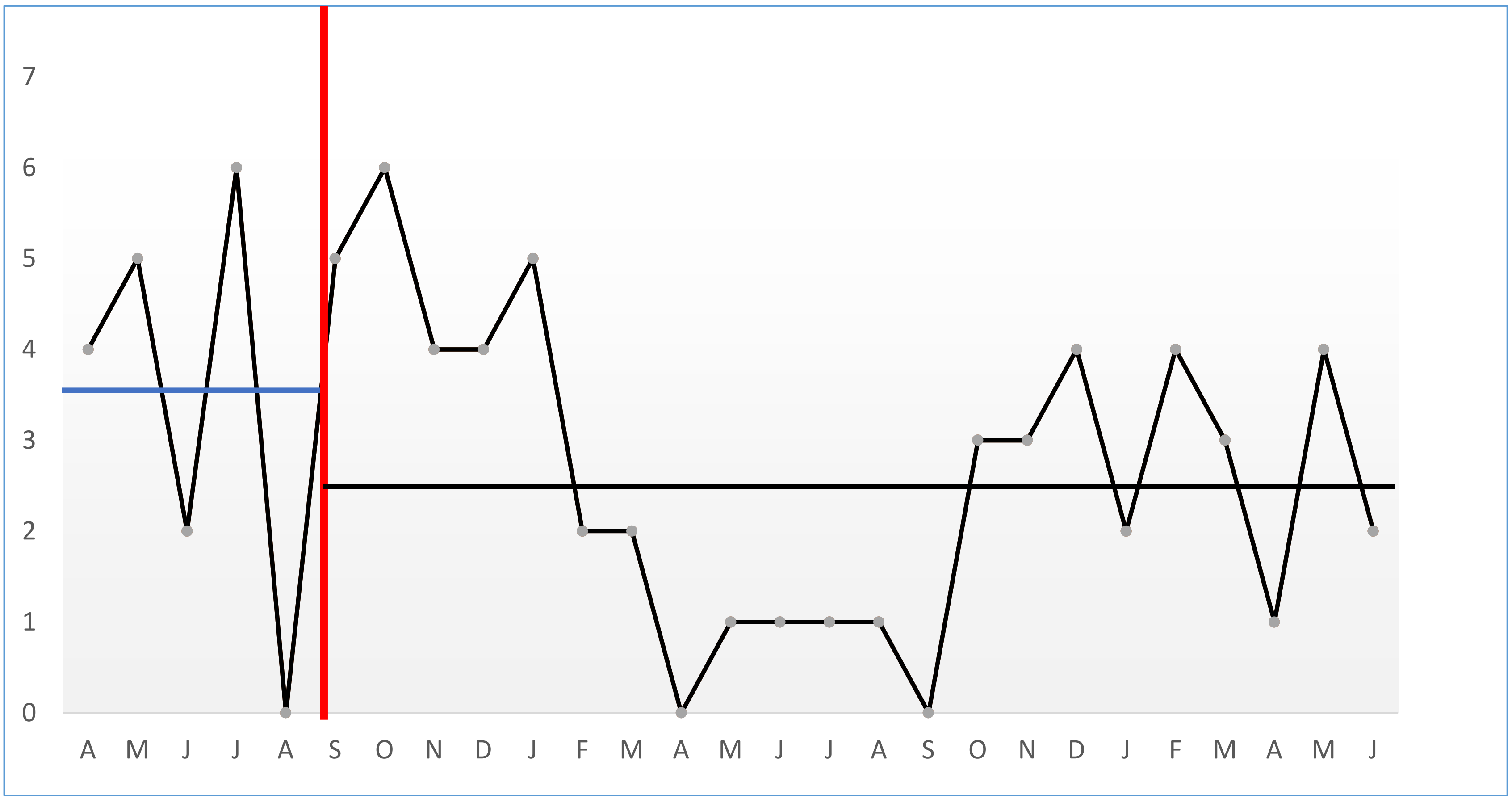
Code Blue Rate/1000 Admits



PRE AEGIS POST AEGIS

Cardiology Ward Codes 2015- 2017

EWS deployment



2015 2016 2017

Integrated EMR

- Epic Sepsis Model is a prediction model that has been implemented in hundreds of hospitals
- Uses a proprietary logistic regression model

- First published independent evaluation: a retrospective cohort study of 38,455 hospitalizations at the University of Michigan
- AUC only 0.63 (95% CI 0.62-0.64), which is lower than most and worse than reported by the developer
- Sensitivity only 33% (of those missed, clinicians administered timely antibiotics in 60%)
- PPV of 12% (number needed to evaluate = 8)
- 18% of all hospitalized patients had an alert generated at some point in their journey

Rise of the Machines

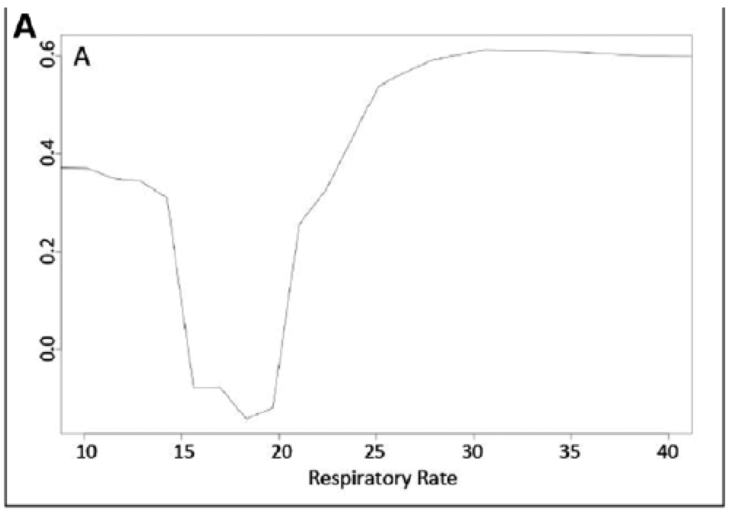
- Machine learning algorithms (AI) were tested against logistic regression models and to a commonly used EWS (MEWS) in an observational cohort study of 269,999 hospitalized ward patients in the US

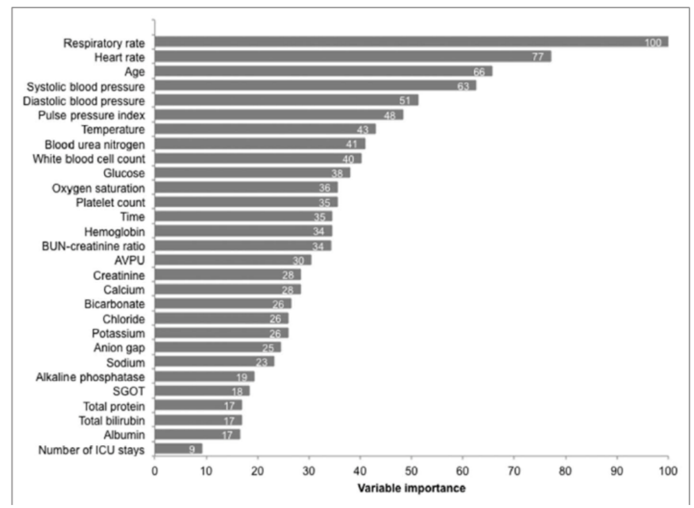
- AI (random forest and gradient boosted): AUC 0.94 for death, 0.83 for cardiac arrest, 0.79 for ICU transfer
- MEWS (comparator): AUC 0.70 overall

(Churpek et al. Crit Care Med 2016;44:368-375)

Black box?

- The most important predictor variables in the AI model were resp rate, heart rate, SBP and age – face validity





- AI model had best calibration (agreement between predicted and observed probability of events)

- AI model generated the fewest alerts at any given level of sensitivity – the least amount of potential alert fatigue

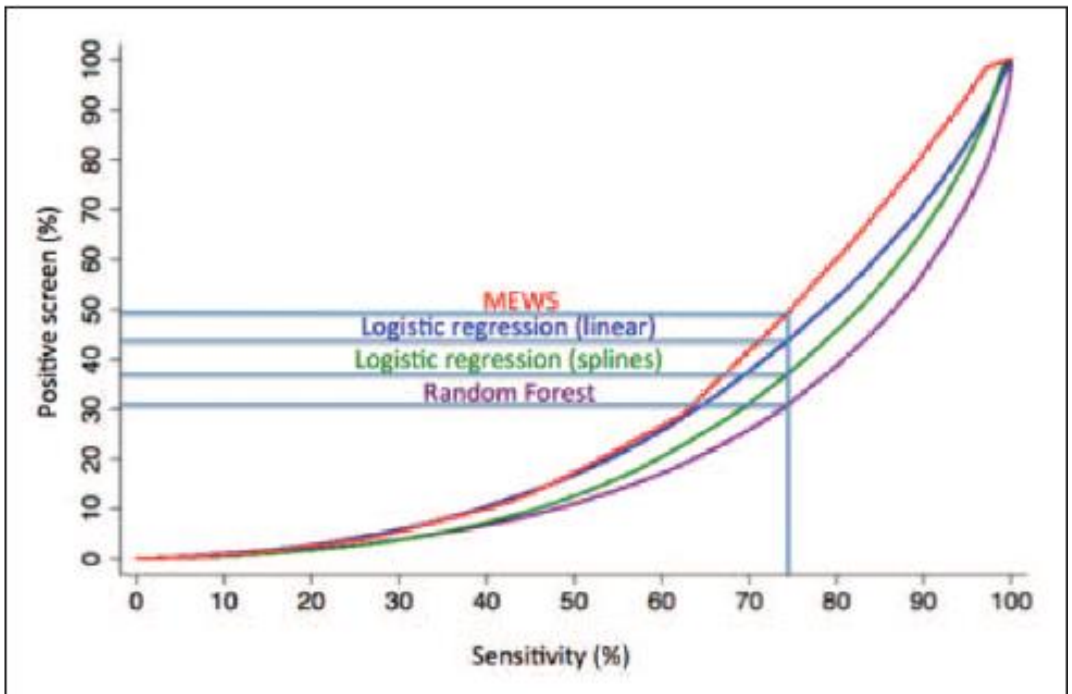


Figure 2. Graph illustrating model sensitivity by the percent of observations above a score threshold (i.e., positive screen) for the Modified Early Warning Score (MEWS), logistic regression models, and random forest model in the validation cohort.

AI - RCT data

Small open-label RCT (142 patients) of a machine learning (AI) algorithm vs Epic Sepsis Model (control) in 2 medical/surgical ICUs at UCSF

Charge RN called if either system alerted and followed a standard severe sepsis assessment and treatment bundle

Outcomes: hospital LOS, mortality

Table 2 Differences in hospital LOS, ICU LOS, and in-hospital mortality between the experimental and control groups

Outcome	Control (n=75)	Experimental (n=67)	Amount of reduction	P value
Hospital LOS (days)	13.0 (1.23)	10.3 (0.912)	2.30 days	0.042
ICU LOS (days)	8.40 (0.881)	6.31 (0.666)	2.09 days	0.030
In-hospital mortality rate	21.3% (4.76%)	8.96% (3.51%)	12.3%	0.018

The mean and the standard error (in parentheses) for each outcome are noted in the table. All outcomes demonstrate statistically significant reductions when using the machine learning algorithm ($p<0.05$).
ICU, intensive care unit; LOS, length of stay.

Unity Health Toronto: St. Michael’s Hospital

- St. Michael’s Hospital
  - Tertiary care teaching hospital in downtown Toronto
  - Established in 1892 with the founding goal of taking care of the sick and the poor of Toronto’s inner city
  - 1 of two adult trauma centres in the GTA
  - ~500 beds and numerous outpatient clinics
    - > 6,000 staff
    - > 900 physicians; > 1,600 nurses
  - Approximate annual patient volumes
    - > 75,000 ED visits
    - > 500,000 ambulatory visits
    - > 25,000 inpatient visits
  - Dedicated Data Science and Advanced Analytics team
  - Fully affiliated with the University of Toronto
    - Part of the Toronto Academic Health Sciences Network (TAHSN)

1 in 12 internal medicine patients will die in hospital: what can be done?

↑ Monitoring

Antibiotics?

CCRT

Palliative Care

Communicate

Mr. DV

Can we predict who will die so we can intervene earlier?

73 year-old retired banker
Inflamed gallbladder (cholecystitis): internal medicine patient

Had advanced gastrointestinal procedure
Plan for discharge home next day

MD called at 18:30
Mr. DV had shortness of breath, MD ordered chest x-ray and labs

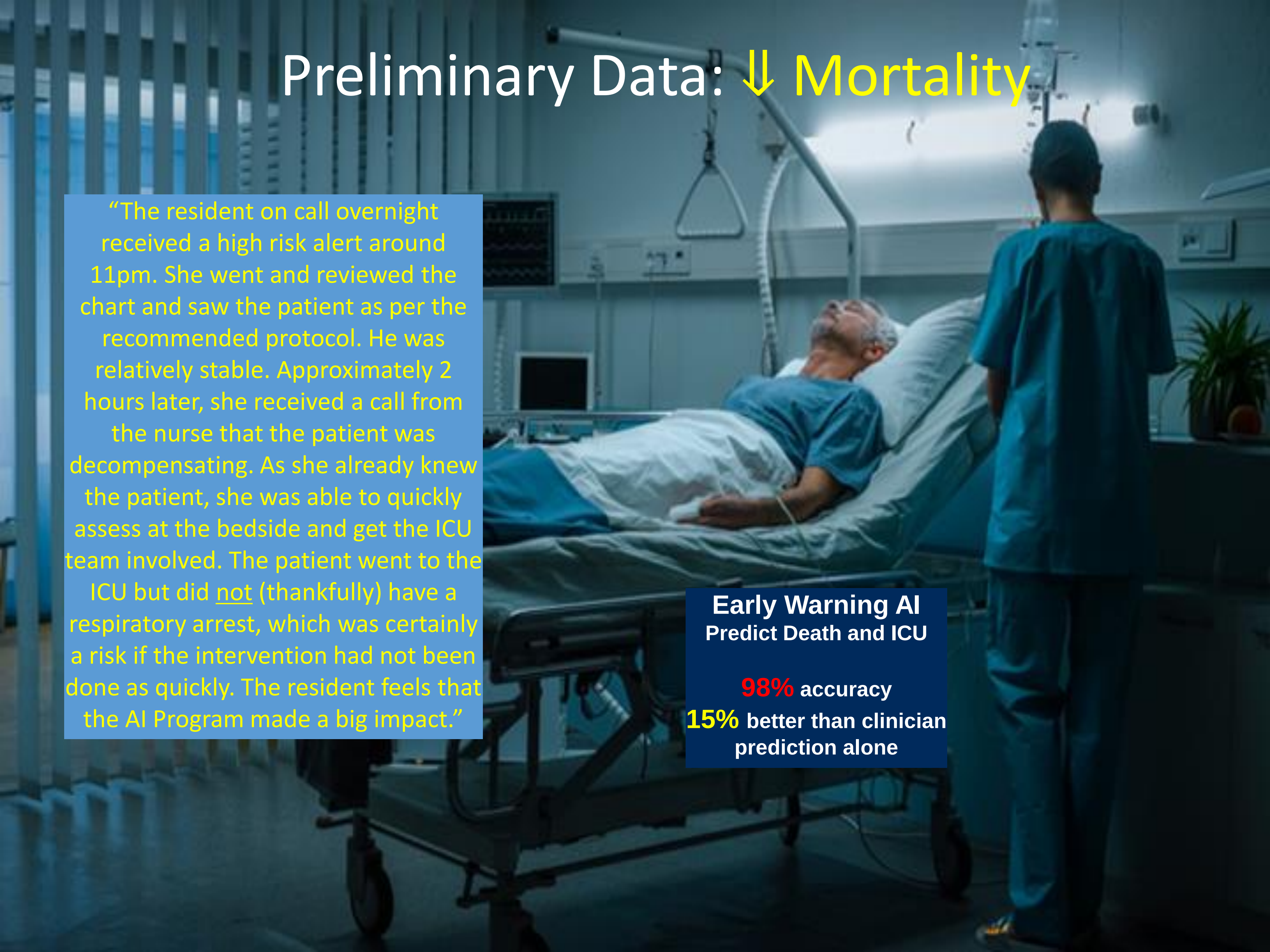
Vital signs checked twice overnight (midnight and 06:00)

MD called at 08:30 for decreased blood pressure, distres
ICU team was called

Mr. DV did not want ICU and died that day

Family distraught:
"We would never have left his bedside"

Preliminary Data: ⇓ Mortality



"The resident on call overnight received a high risk alert around 11pm. She went and reviewed the chart and saw the patient as per the recommended protocol. He was relatively stable. Approximately 2 hours later, she received a call from the nurse that the patient was decompensating. As she already knew the patient, she was able to quickly assess at the bedside and get the ICU team involved. The patient went to the ICU but did not (thankfully) have a respiratory arrest, which was certainly a risk if the intervention had not been done as quickly. The resident feels that the AI Program made a big impact."

Early Warning AI
Predict Death and ICU

98% accuracy
15% better than clinician prediction alone

Monitors Hourly:
Demographics
Labs
Vitals

Intervention Checklist

- Reassess patient
- ↑ vitals
- Goals of care
- Consider sepsis
- Consider involving ICU/CCRT, or palliative care

Machine Learning (XGBoost) Model Classifies Patients:
Low
Medium
High

Alarm is triggered!
Notifications to MD, RN, Other

Care pathway initiated

High Risk Alerts:
1-2 x per day

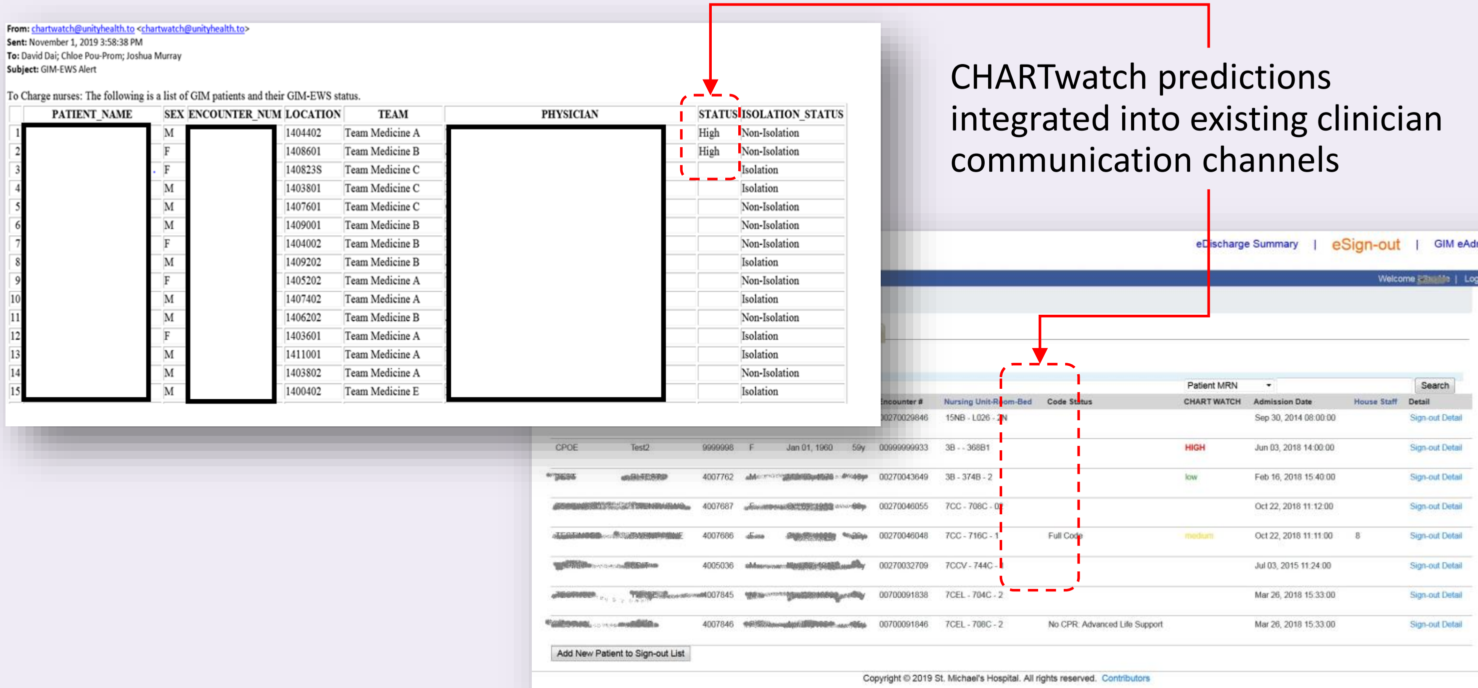
CHARTwatch flags high risk patients and integrates into established clinician communication mediums with a well-defined care pathway

Integrated into existing communication channels (email)

Alerts sent through SPOK communication

Embedded in staffing process: High risk clients are well distributed across RNs

A defined care pathway was implemented for any high risk client


From: chartwatch@unityhealth.to <chartwatch@unityhealth.to>
Sent: November 1, 2019 3:58:38 PM
To: David Dai; Chloe Pou-Prom; Joshua Murray
Subject: GIM-EWS Alert

To Charge nurses: The following is a list of GIM patients and their GIM-EWS status.

	PATIENT_NAME	SEX	ENCOUNTER_NUM	LOCATION	TEAM	PHYSICIAN	STATUS	ISOLATION_STATUS
1	[redacted]	M	[redacted]	1404402	Team Medicine A	[redacted]	High	Non-Isolation
2		F		1408601	Team Medicine B		High	Non-Isolation
3		F		140823S	Team Medicine C			Isolation
4		M		1403801	Team Medicine C			Isolation
5		M		1407601	Team Medicine C			Non-Isolation
6		M		1409001	Team Medicine B			Non-Isolation
7		F		1404002	Team Medicine B			Non-Isolation
8		M		1409202	Team Medicine B			Isolation
9		F		1405202	Team Medicine A			Non-Isolation
10		M		1407402	Team Medicine A			Isolation
11		M		1406202	Team Medicine B			Non-Isolation
12		F		1403601	Team Medicine A			Isolation
13		M		1411001	Team Medicine A			Isolation
14		M		1403802	Team Medicine A			Non-Isolation
15		M		1400402	Team Medicine E			Isolation

CHARTwatch predictions integrated into existing clinician communication channels

Some Considerations

- Deployment / Performance Metrics / Evaluation
  - Model customization and performance: training + precision, recall, false positive, false negative
  - Workflow considerations: false alarms, reporting frequency
  - Clinical validation: does the model perform better than 'usual practice'?
  - Silent testing / piloting
  - Model maintenance: ongoing monitoring and refinement
  - Education: algorithms aren't perfect and neither are clinicians – be conservative!

- Privacy and Confidentiality
  - Identified vs de-identified data
  - Data governance and access

- Risk and Liability
  - Unintended consequences
  - Discordant actions

- Bias and Equity
  - Model performance across age, sex, and clinical features
  - What about race, socioeconomic status, education level, etc?

Thank you for joining us today

Feedback? Suggestions for the next topic? — **Submit ideas in our evaluation survey (Link in chat)**

Subscribe — **Critical Care Services Ontario**

Follow — **@CriticalCareON**

Join — Eventbrite

February 2023

Health Human Resource Strategies

Questions? — **info@ccso.ca**

Hosted by

CCSO | SMPCO

ccso.ca