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ORIGINAL RESEARCH

Impact of predictive analytics based on continuous cardiorespiratory monitoring in a surgical and trauma intensive care unit

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Abstract

Predictive analytics monitoring, the use of patient data to provide continuous risk estimation of deterioration, is a promising new application of big data analytical techniques to the care of individual patients. We tested the hypothesis that continuous display of novel electronic risk visualization of respiratory and cardiovascular events would impact intensive care unit (ICU) patient outcomes. In an adult tertiary care surgical trauma ICU, we displayed risk estimation visualizations on a large monitor, but in the medical ICU in the same institution we did not. The risk estimates were based solely on analysis of continuous cardiorespiratory monitoring. We examined 4275 individual patient records within a 7 month time period preceding and following data display. We determined cases of septic shock, emergency intubation, hemorrhage, and death to compare rates per patient care pre-and post-implementation. Following implementation, the incidence of septic shock fell by half ($p<0.01$ in a multivariate model that included age and APACHE) in the surgical trauma ICU, where the data were continuously on display, but by only 10% ($p=$NS) in the control Medical ICU. There were no significant changes in the other outcomes. Display of a predictive analytics monitor based on continuous cardiorespiratory monitoring was followed by a reduction in the rate of septic shock, even when controlling for age and APACHE score.

Keywords Predictive analytics monitoring · Continuous display · Big data · Sepsis

1 Introduction

Surgical trauma intensive care unit (ICU) patients are at high risk for unexpected clinical deterioration. Subacute illnesses, such as hemorrhage, sepsis, or respiratory decompensation occur in up to 10% of ICU patients and increase the length of stay and the death rate by several-fold [1, 2]. Decisions to treat in early stages of subacute illness may improve clinical outcomes [3], yet recognizing early stages continues to be elusive for clinicians. Drawing attention to patients who may be deteriorating can allow for earlier clinical intervention and improved patient outcomes [4, 5].

We developed a visual representation of fold-risk for clinical deterioration and continuously display this representation on LCD monitors within patient care units. Known as CoMET® (Continuous Monitoring of Event Trajectories; Advanced Medical Predictive Devices, Diagnostics, and Displays, Charlottesville, VA), these displays were employed on large screens in an adult surgical and trauma ICU (STICU) at a tertiary care academic medical center since June 2015. CoMET utilizes multivariate predictive models based on, for example, heart rate, respiratory rate (RR), SpO_2, the RR–SPO_2 correlation coefficient, detrended fluctuation analysis of RR intervals [6, 7] density scores, and the standard deviation of RR intervals gleaned from continuous cardiorespiratory models taken every 2 s with model risk updates every 15 min. Only continuous cardiorespiratory monitoring data are used in the risk estimations. As shown in Fig. 1, we display the fold-increase in risk of respiratory failure leading

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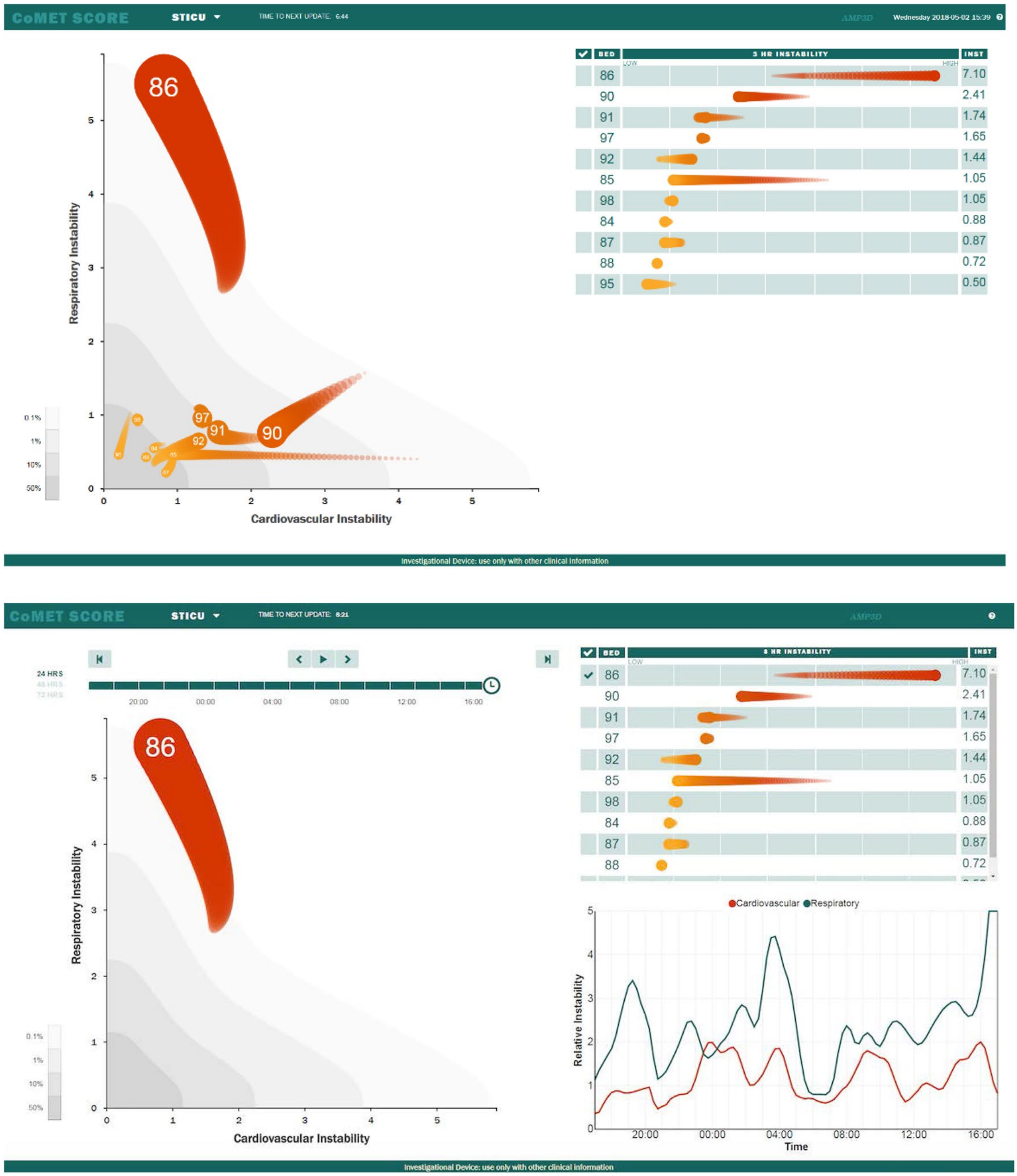

Fig. 1 (Top) Visual representation of the CoMET display as it appeared on a large screen monitor in the surgical ICU. Units on the Respiratory and Cardiovascular instability axes represent the fold-increase in risk compared to average for emergency intubation and hemorrhage, respectively. Each bed is represented by a comet with the bed number in the head. The head of the comet represents the risks at the current time, and the tail is 3 h long. (Bottom) a patient in bed 86 has been selected for individual inspection. This patient's respiratory (green) and cardiovascular (orange) instability over the preceding 24 h is displayed in the bottom right. The respiratory instability rose from average risk (onefold) to fivefold average risk over the 10 h prior to emergency intubation at 19:35. Similarly, cardiovascular instability fluctuated between average and twofold average; a blood culture for suspicion of infection was ordered at 18:22. These data were taken from recorded real-time monitoring performed during this patient's hospital stay, prior to the period that CoMET was displayed in the SICU

to urgent unplanned intubation [8] on the vertical axis and the fold-increase in risk of hemorrhage leading to large unplanned transfusion [9] on the horizontal axis. Based on feedback from ICU bedside clinicians, the axes are labeled "Respiratory instability" and "Cardiovascular instability," respectively. Previously, we showed that the risk of sepsis was more correlated with the respiratory failure model in the STICU, and with the hemorrhage model in the Medical ICU (MICU) [1]. We hypothesized that display of this predictive analytics monitor would improve patient outcomes based on the premise of earlier detection and clinical action.

2 Methods

2.1 Study design

We conducted a retrospective cohort study to assess differences in clinical outcomes pre-and post-implementation of the CoMET display where the STICU served as the test unit (i.e., CoMET displayed) compared to the MICU, the control unit (i.e., no display), at a large tertiary care academic center. We reviewed individual patient records from all admissions from December 2014 to February 2016 to the medical and surgical intensive care units (n = 4275) using the Epic electronic medical record and clinical databases (e.g., clinical data warehouse, blood bank records), we collected the following data: APACHE score, age, gender, length of ICU and hospital stay, mortality, packed red blood cell transfusion, and identified septic shock and emergent intubation cases.

2.2 Clinical outcomes of interest

2.2.1 Sepsis cases (Fig. 2)

We used Surviving Sepsis Campaign guidelines where the suspicion of infection was a blood culture with documentation in the record supporting the clinical intent. This is a Sepsis-2 definition. To identify cases of septic shock, patient records were first screened for mean arterial pressure less than 60 mm Hg despite fluid resuscitation, or vasopressor administration > 8 h after time of admission. We then sought blood culture orders for suspicion of infection within 48 h prior to or after being placed on vasopressors. Finally, if a patient met criteria for severe sepsis (2/4 SIRS plus organ failure) within 12 h prior to or after their blood culture order, the admission was recorded as an instance of septic shock. Patients admitted with a shock syndrome, as indicated by admission diagnosis and/or treatment with vasoactive medications within 8 h of ICU admission, were excluded.

2.2.2 Emergent intubation cases (Fig. 3)

Respiratory failure was defined as emergent or urgent intubation occurring after admission to the intensive care unit. A flowsheet in our electronic medical record (the Adult Respiratory Accordion) was examined for mechanical ventilation during each patient's ICU stay. Intubations occurring in the field, emergency department (ED), operating room (OR), another inpatient unit, or in an outside hospital were excluded, as indicated by a patient arriving to the unit on mechanical ventilation. If an intubation was identified in the Adult Respiratory Accordion, the Respiratory Therapy note or the Intubation Procedure note were searched for the indication for intubation. If a clinician documented the event as emergent or urgent, it was recorded as an instance of respiratory failure.

2.2.3 Hemorrhage

Hemorrhage was defined as infusion of three units of packed red blood cells within 24 h. Data was obtained from the institution's blood bank records.

2.2.4 Mortality

Mortality was defined as death occurring in the intensive care unit during that admission. Data were obtained from the institution's Data Warehouse.

2.2.5 Length of stay

Data on patient length of stay were obtained from the institution's clinical data repository.

2.3 Statistical methods

Rate ratio, or events per patient per day post-CoMET implementation divided by events per patient per day pre-CoMET implementation, was calculated for each outcome of interest. We compared groups using a Wilcoxon rank sum test for continuous variables and using the pooled sample proportion for rate data. Confidence intervals for individual event rates were based on a Poisson distribution. An exact binomial test was used to determine the confidence intervals and *p*-values for rate ratios. A *p*-value < 0.05 was considered statistically significant. We used R version 3.3 software.

3 Results

3.1 Patent population

From December 1, 2014 to February 1, 2016, there were 1747 admissions to the STICU and 2528 admissions to the MICU. These data represented 5780 SICU patient days and 9922 MICU patient days. Demographics appear in Table 1. 1410 and 1972 patients, for the STICU and MICU, respectively, met inclusion criteria for evaluation for septic shock (i.e., were not admitted with any shock syndrome). All admissions were evaluated for respiratory failure, hemorrhage, death, and length of stay.

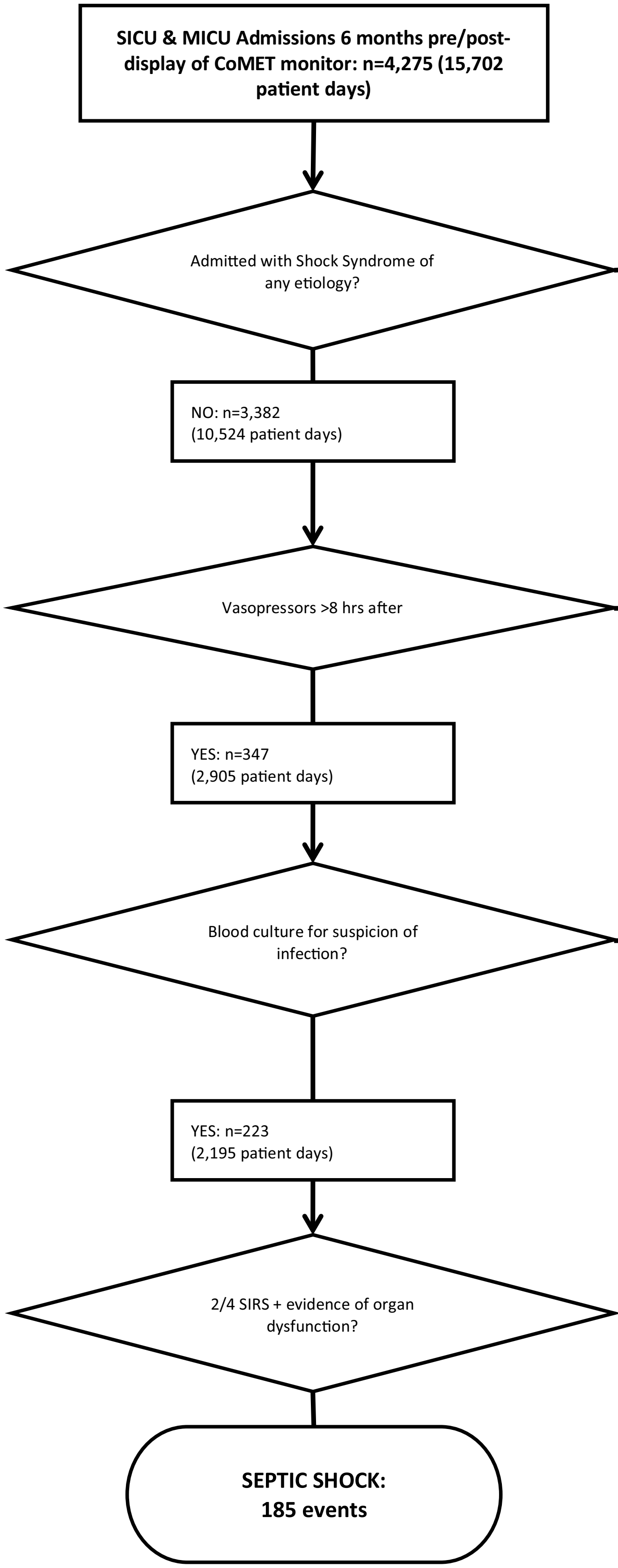

Fig. 2 Flowchart depiction of the methodology for evaluation for septic shock in the electronic medical record

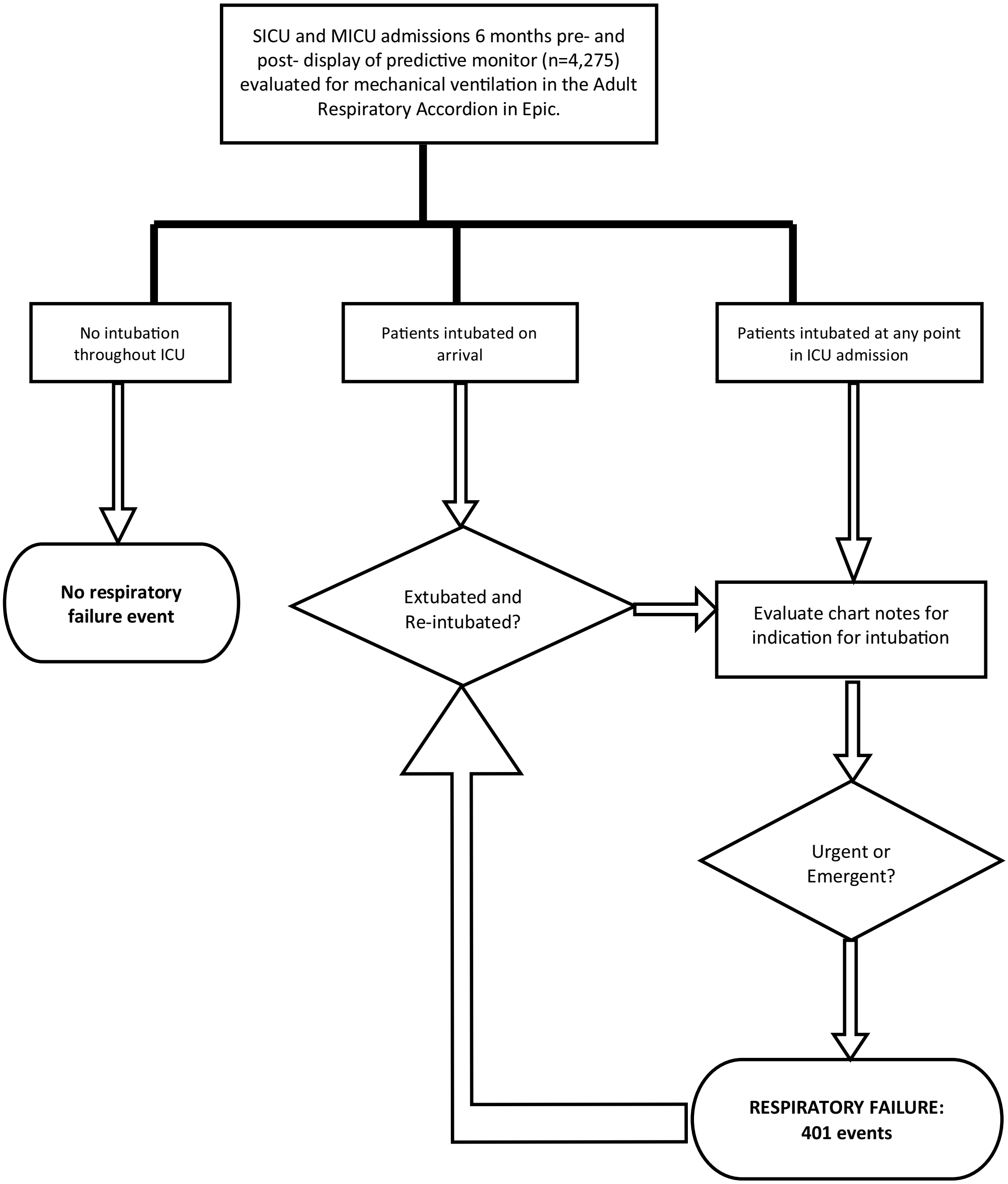

Fig. 3 Flowchart depiction of methodology for the evaluation of respiratory failure events in the electronic medical record

3.2 An example of the predictive analytics monitoring display

A representative case illustrating a situation in which CoMET may have impacted a patient's course, is demonstrated in Fig. 1. This patient ultimately underwent emergent intubation and a blood culture order for suspicion of infection. We note that the respiratory instability score rose from average (onefold) to fivefold average risk over the 10 h prior to both respiratory failure and the clinical concern for sepsis. We hypothesized that the presence of the CoMET monitor would have prompted an unscheduled clinician visit to the patient for a more in-depth evaluation, which would have facilitated an earlier intervention, possibly averting adverse outcomes.

3.3 Event rates before and after display implementation

Figure 4 and Table 2 show the major results of the study. The number of events and the event rate per patient day are given for the periods before and after implementation of the predictive analytics monitoring in the STICU. The rate of septic shock in the STICU decreased by more than half after the display of the monitor (rate ratio = 0.478, p = 0.012, Table 2). In the MICU, the rate fell by 10%, a non-significant

Table 1 Demographics of the study population showing median (IQR)

	STICU			MICU		
	Pre-CoMET	Post-CoMET	p	Pre-CoMET	Post-CoMET	p
Admits	840	907		1204	1324	
ICU stay (days)	1.6 (0.9–3.2)	1.6 (0.9–3.2)	0.917	2.3 (1.1–4.5)	2.2 (1.2–4.4)	0.837
Shock on admit	16%	22%	0.002	21%	23%	0.453
Male	59%	60%	0.760	55%	54%	0.729
Age	59 (46–70)	61 (48–72)	0.090	62 (52–72)	63 (50–73)	0.990
APACHE	9 (5–14)	9 (5–14)	0.639	12 (6–17)	11 (6–17)	0.482
CCI	2 (0–6)	2 (0–5)	0.257	4 (2–8)	4 (2–8)	0.045
DNR	6%	8%	0.193	27%	29%	0.354
DNI	0.10%	0.20%	0.609	1.20%	2.90%	0.003

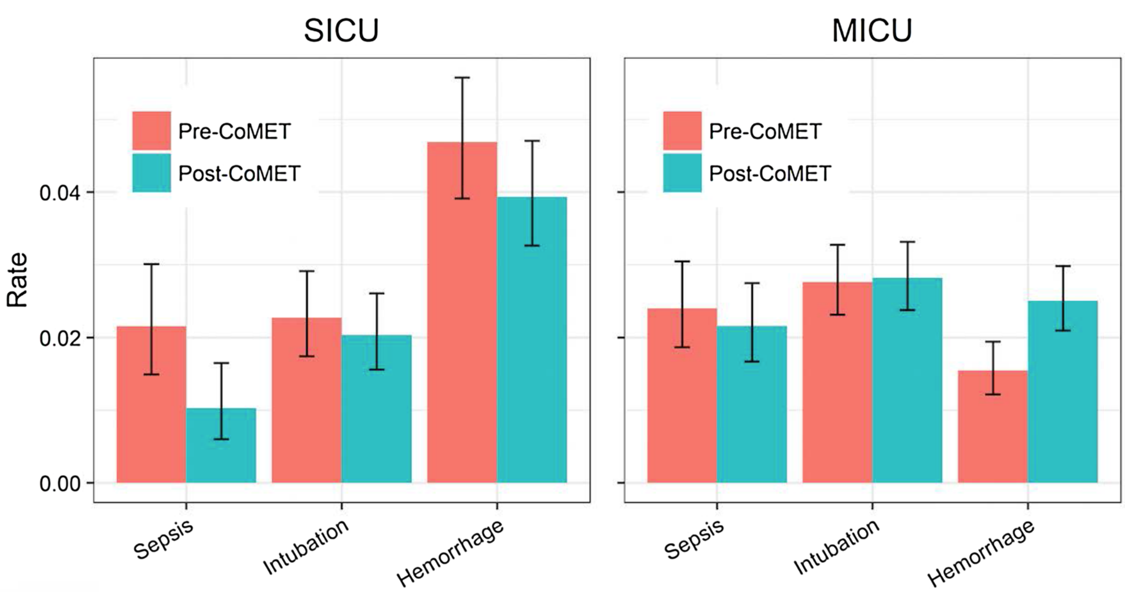

Fig. 4 Comparison of event rates between the periods prior to risk monitor display (red) and after risk monitor display (blue), categorized by event of interest and unit; error bars represent confidence intervals for each rate, based on a Poisson distribution

Table 2 Events, event rates per patient days, and ratios of event rates before and after CoMET display with confidence intervals and *p* values

Event	Unit	Pre CoMET Event, rate	Post CoMET Event, rate	Rate ratio	P value
Septic shock	STICU	34, 0.022	17, 0.010	0.478 (0.250–0.880)	0.012
Septic shock	MICU	67, 0.024	67, 0.022	0.899 (0.631–1.281)	0.546
Respiratory failure	STICU	62, 0.023	62, 0.020	0.895 (0.619–1.294)	0.59
Respiratory failure	MICU	132, 0.028	145, 0.028	1.020 (0.801–1.302)	0.904
Hemorrhage	STICU	128, 0.047	120, 0.039	0.839 (0.649–1.085)	0.182
Hemorrhage	MICU	74, 0.015	129, 0.025	1.619 (1.208–2.185)	0.001
Mortality	STICU	55, 0.020	70, 0.023	1.140 (0.789–1.653)	0.475
Mortality	MICU	197, 0.041	225, 0.044	1.061 (0.872–1.291)	0.559

change. The rates of respiratory failure and mortality did not change significantly in either unit when comparing the periods before and after monitor display (Table 2). The rate of hemorrhage did not change in the STICU and increased in the MICU (p = 0.001, Table 2). The average hospital length of stay did not change after display of the predictive analytics monitor (see Table 1).

To test the possibility that the fall in septic shock in the STICU was due to a large change in the patient demographics and severity of illness during the study period, we used multivariable logistic regression. The small number of septic shock events—34 before implementing the predictive analytics monitoring display and 17 afterwards—allowed only two additional variables besides the presence or absence of display in the analysis. We chose age and APACHE score to reflect important risk factors for STICU outcomes. We found that the fall in rate of septic shock remained significant after accounting for these other risk factors ($p = 0.016$), suggesting that the display independently impacted the outcome.

4 Discussion

We evaluated the impact of predictive analytics monitoring based only on continuous cardiorespiratory monitoring on patient outcomes in the ICU environment. We found a decreased rate of septic shock in the Surgical ICU where real time risk estimates for respiratory and cardiovascular instability were displayed as compared to a Medical ICU where it was not. These results remained statistically significant even after adjusting for age and APACHE score. We did not observe statistically significant differences in the rates of respiratory failure, hemorrhage, mortality, or length of stay in the year-long, single ICU study. The results are consistent with the aim of predictive analytics monitoring, which is not so much to prevent the critical illness itself—sepsis, hemorrhage or respiratory failure—as it is to allow early detection and reduce the complications, such as septic shock.

Advances in continuous bedside monitoring technology capabilities make a wealth of data available to healthcare providers' evaluation. These data form the foundation for computational algorithms that integrate real-time bedside monitor physiologic data to provide early warning of potentially catastrophic physiologic events [1, 8, 10–18]. In premature infants, for example, continuous display of the fold-increase in risk (relative to the average risk) of neonatal sepsis using a predictive analytics monitor decreased mortality in a large randomized trial of 3000 very low birth weight infants [19]. The development, utilization, and testing of continuous predictive analytics monitoring in adult ICU populations are less well addressed, and produced inconsistent results [20–26]. For example, display of an instability score did not change the rate of major events in 201 high-risk medical and surgical ICU patients compared to 201 controls [26], but the same intervention led to reduced instability episodes in 306 patients compared to 326 controls in a subsequent study [22]. Most recently, display of a vital signs-based risk score led to reduced length of stay and mortality in 67 ICU patients compared to 75 controls [25]. These algorithms all used hourly vital signs entered into the electronic health record, often as systemic inflammatory response syndrome (SIRS) criteria, and lab tests. Thus, these studies tested strategies based on static, intermittent measures from patients.

Using data from continuous bedside cardiorespiratory monitoring offers a complementary approach to early warning of patient decline. We and others have integrated continuous physiologic data into care to predict outcomes ranging from complications of subarachnoid hemorrhage to neonatal cardiopulmonary deterioration [1, 8–11, 13–18, 27] while others developed models for early and more accurate sepsis prediction [17, 18, 28–32] and tested them retrospectively. For example, we detected signatures of illness in the bedside monitor physiological data streams in adult ICU patients prior to clinical signs of sepsis, hemorrhage resulting in large transfusion, and respiratory failure resulting in urgent, unplanned intubation [1]. Additionally, we found that subtle physiologic signatures of these events are detectable up to 24-h in advance of clinical deterioration through advanced mathematical analysis of cardiorespiratory dynamics [1, 8, 9, 16, 33].

Our study has several strengths. First, the algorithms were developed using clinical and adverse events identified through individual medical record review [1, 8]. This gold standard is superior to computer database queries for clinical or coding information [34]. In all, more than 8000 individual patient charts were examined for algorithm development and testing. Additionally, we controlled for institutional and other systemic changes in sepsis diagnosis and treatment by examining outcomes in the Medical ICU, that did not have CoMET and employed only conventional care. Finally, CoMET used only continuous physiologic data from the bedside monitors and did not use conventional EHR data elements such as demographics, diagnoses, lab values or nurse-charted vital signs, data prone to delayed entry and missing values [35].

The study also has limitations. This was a retrospective cohort study based on outcome ascertainment conducted at a single center and may yet reflect practice changes unrelated to CoMET. Seasonal variability could not be accounted for because the study period ranged from 7 months pre-intervention to 7 months post-intervention. To counter seasonal effects, we elected to use the neighboring medical ICU as one measure of control. Possible mechanisms unrelated to the predictive analytics monitoring display that might have led to reduced septic shock in one ICU compared to another include staffing (they are very similar, with one attending intensivist per 14–15 beds), different sepsis-specific initiatives in the ICUs (there were none), or different levels of sepsis-specific scrutiny for quality reporting reasons (both units are scrutinized by the same central quality office using the same metrics).

Mechanisms of provider acceptance of continuous predictive analytics monitoring is not well understood, and there is little guidance to promote adoption in practice [36]. Previously, we investigated factors underlying implementation of a predictive analytics monitor in the neonatal ICU that reported fold-increase in risk of neonatal sepsis in the next 24 h. We interviewed 22 clinicians and found that the information was increasingly viewed as important once nurses and physicians routinely collected, documented, and reported the risk score during patient rounds and patient handoffs [37]. Adoption increased further after finding that display of the predictive analytics monitor reduced NICU mortality by more than 20% in a very large randomized trial [19], and by 40% in infants who were diagnosed with sepsis [12].

Similarly, we interviewed 14 Surgical ICU clinicians involved in this study. They expressed hesitancy in responding to a rising risk with direct clinical action because they felt the monitor reported a future state rather than routine 'in the moment' physiologic parameters [36]. Rather, they felt they first must accept that the prediction is sufficiently reliable to support proactive intervention [36]. We found other elements of clinician engagement with predictive analytics monitoring included accepting the reliability of the risk score, understanding the science underlying the algorithm, developing clinical pathways that correspond to varying levels of risk, and integrating the risk score into the electronic medical record as a vital sign [36].

In conclusion, the display of a predictive analytics monitor in a surgical ICU was followed by a reduction in the rate of septic shock that was statistically significant even when controlling for age and APACHE score. We propose that there is clinical value of predictive analytics monitoring, especially when continuous data from bedside monitoring are used.

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Compliance with ethical standards

Conflict of interest MTC and JRM are Chief Science and Chief Medical Officers of and hold equity in Advanced Medical Predictive Devices, Diagnostics, and Displays (AMP3D), Charlottesville, VA. MTC is employed by AMP3D.

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