Original Article

Continuous Cloud-Based Early Warning Score Surveillance to Improve the Safety of Acutely Ill Hospitalized Patients

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ABSTRACT

Introduction: This study sought to evaluate the impact of changes made to the process of continually screening hospitalized patients for decompensation.

Methods: Patients admitted to hospital wards were screened using a cloud-based early warning score (modified National Early Warning Score [mNEWS]). Patient with mNEWS ≥7 triggered a structured response. Outcomes of this quality improvement study during the intervention period from February through August 2018 (1741 patients) were compared with a control population (1,610 patients) during the same months of 2017.

Results: The intervention group improved the time to the first lactate order within 24 hours of mNEWS ≥7 ($p < .001$), the primary outcome, compared with the control group. There was no significant improvement in time to intensive care unit (ICU) transfer, ICU length of stay (LOS), or hospital mortality. Among patients with a lactate ordered within 24 hours, there was a 47% reduction of in-hospital mortality (odds ratio 0.53, 95% confidence interval 0.3–0.89, $p = .02$) and a 4.7 day reduction in hospital LOS ($p < .001$) for intervention versus control cohorts.

Conclusions: Cloud-based electronic surveillance can result in earlier detection of clinical decompensation. This intervention resulted in lower hospital LOS and mortality among patients with early detection of and intervention for clinical decompensation.

Keywords: sepsis, infection, quality improvement, cloud-based monitoring, early warning score

Introduction

Delays in identifying and treating decompensating patients on hospital wards outside of the intensive care unit (ICU) contribute to increased morbidity and mortality.[1-3] Sepsis is a major cause of deterioration and mortality in this population, with the Surviving Sepsis Guidelines recommending screening of all inpatients for the development of sepsis.[4,5] Some types of rapid response teams (RRTs) can reduce mortality and are now standard hospital practice for evaluating and expediting treatment of deteriorating patients outside of the ICU.[6,7] These systems generally rely on a member of the treatment team or family member recognizing clinical decompensation and activating the RRT.

Hospitals are increasingly using software algorithms to monitor patients for clinical decompensation to improve sepsis detection, timely intervention, and outcomes.[8,9] Electronic medical records (EMRs), now used in most U.S. hospitals, provide a continuous flow of personalized clinical data for monitoring decompensation.[10] Early warning scores based on vital signs and other physiological parameters can predict decompensation and need for ICU care.[8,11,12] The National Early Warning Score (NEWS) is a validated measure for decompensation and widely used in health systems across North America and the United Kingdom.[11-14] Although early warning scores can predict decompensation

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within the hospital, there is no consensus on how best to deploy them within clinical settings.

Within our hospital, delays in identifying decompensating patients outside of the ICU were identified as factors contributing to increased mortality and length of stay (LOS). Sepsis is a leading cause for decompensation, and evaluation of serum lactate levels is a cornerstone of timely sepsis evaluation.[4] As a result, the time to a lactate order is a key outcome of an effective intervention process. Furthermore, delays to ICU transfer have been associated with higher mortality.[15] We implemented an intervention using a cloud-based software system for earlier assessment of decompensation among all patients within the hospital. The cloud-based monitoring system used an early warning threshold for triggering a standardized RRT evaluation for any decompensating patient.

The objective of this study was to assess a quality improvement process of identifying decompensating patients outside of ICU, namely inclusion of a continuous cloud-based early warning system to activate a RRT, by measuring the time to lactate ordering and transfer to ICU, with an overall goal of decreasing mortality and LOS.

Methods

Context

This is a quality improvement study. The intervention was performed at an 850-bed urban tertiary care academic hospital that does not provide trauma or obstetrics services. During the control cohort period of February 19 through August 31, 2017, the hospital used a standard process similar to other large hospitals (see Figure 1, Supplemental Digital Content, http://links.lww.com/JHQ/A117). Once patients were admitted to the hospital outside the ICU, they were monitored by nursing staff, receiving vital sign checks every 4–12 hours based on the admitting physician orders. The RRT within the hospital included two ICU-trained nurses providing 24-hour evaluation whenever concerns arose that a patient was deteriorating. In addition, the hospital EMR (Epic 2015) screened inpatients for possible sepsis using an embedded systemic inflammatory response syndrome (SIRS) score. Once a patient had a SIRS score ≥2, the EMR would send an alert within the patient record that was available to any physician accessing the patient's chart.[16] The physician could then evaluate the patient, or if needed could call for the RRT to evaluate the patient. In addition to the RRT, there was an established medical emergency team (MET) consisting of a critical care physician and staff who could provide critical care support outside of the ICU. Root cause analysis of sepsis and other decompensated patients indicated delayed identification of deterioration because of this antiquated, variable, and unreliable process of RRT activation. Hospital leadership found that sepsis outcomes were inferior to other comparable hospitals. This led the hospital to standardize and improve the early identification of decompensating patients from sepsis and other etiologies.

Improvement

To address this need, the hospital partnered with a third-party software company to collect and analyze clinical data from the EMR. Although not studied previously to improve sepsis outcomes, this cloud-based screening software provided the means to continuously screen patients and immediately alert the RRT. Concern for hospital sepsis outcomes prompted hospital administration to apply the new process to the entire hospital for this pilot period. An improvement team was established, including members from hospital administration, critical care physicians, hospital quality improvement professionals, RRTs, nurses, pharmacists, and academic partners working together to evaluate deficiencies and design and implement improvements. The intervention and new process (see Figure 1, Supplemental Digital Content, http://links.lww.com/JHQ/A117) began with an effort to standardize patient vital sign assessment and documentation to every 4 hours within the EMR throughout the acute care floors. The cloud-based software continuously screened vital signs of all patients outside of the ICU, using an early warning score. The NEWS is an early warning score combining temperature, pulse rate, systolic blood pressure, respiratory rate, oxygen saturation, need for oxygen supplementation, and level of consciousness.[13,14] A lack of standardized level of consciousness evaluation throughout the hospital led to its omission from the calculated score; thus modified NEWS (mNEWS) was used.

If the cloud-based software detected mNEWS ≥7, then a direct page was sent to the RRT with the patient room number and score. This score was selected as the trigger for the RRT because calculations showed a lower, more sensitive threshold mNEWS would result in an excessive number of patients needing RRT evaluation to detect one patient needing to be moved to the ICU. The RRT immediately assessed the patient at the bedside, rechecked vital signs, and recalculated the mNEWS. If

the patient had mNEWS ≥5, a point of care lactic acid level was drawn by the RRT. If the patient had mNEWS ≥7 or an elevated lactic acid (≥2 mmol/L), then the MET was called to emergently evaluate the patient. The MET intervened at the bedside or rapidly transferred the patient to the ICU at their discretion. If the patient had mNEWS ≥5 without lactic acid elevation, then the RRT informed the primary physician.

This intervention was initiated on February 19, 2018, and data were collected until August 31, 2018 (intervention period). Data during the intervention cohort period were compared with the control cohort period from February 19, 2017 to August 31, 2017. During the 2017 control period, there were 15,118 patient observations with 1,741 unique patients with an mNEWS value ≥7, whereas during the 2018 intervention period, there were 15,174 observations with 1,610 unique patients with an mNEWS value ≥7. For instances of multiple admissions with an mNEWS value ≥7 for a single patient (12.6% of observations in 2017 and 11.3% of observations in 2018), only the first admission was retained.

The project was submitted and approved by the local institutional review board and was granted a waiver of consent (H-43591).

Measures

Demographic and outcome data were obtained from the third-party software for both control and intervention cohorts. Primary outcomes were (1) time (in hours) to the first lactate order within 24 hours of mNEWS ≥7, (2) time (in hours) to ICU transfer within 48 hours after mNEWS ≥7, (3) lactate ordered within 24 hours of mNEWS ≥7 (yes/no), and (4) ICU transfer within 48 hours mNEWS ≥7 (yes/no). Secondary outcomes were (5) in-hospital mortality (yes/no), (6) ICU LOS after ICU transfer after mNEWS ≥7 (in days), and (7) hospital LOS (in days). The Charlson Comorbidity Index (CCI) is a method of categorizing comorbidities of patients based on the *International Classification of Diseases diagnosis codes* found in administrative data and was used to measure burden of disease. Higher scores on the CCI predict a greater burden. Studies consistently demonstrate that the CCI is a valid indicator of mortality.[17] This article examined the CCI as a potential covariate.

Statistical Analysis

We compared patients in intervention versus control cohorts on gender, highest mNEWS value, and whether one had any ICU stay before mNEWS ≥7 using chi-square tests. In addition, we compared patients in intervention versus control cohorts on age and the CCI using independent samples *t*-tests. Unadjusted outcome models were repeated, controlling for variables that significantly differed between cohorts.

Univariate time-to-event analyses were performed, using discrete-time Cox regression models (SAS PROC PHREG) to evaluate differences between the intervention and control cohorts in the continuous primary outcomes of the time to the first lactate order within 24 hours of mNEWS ≥7 and time to ICU transfer within 48 hours of mNEWS ≥7. Participants with no lactate ordered (or who had a lactate ordered at least 24 hours after mNEWS ≥7) were censored at 24 hours. Similarly, participants not transferred to the ICU (or transferred >48 hours later) were censored at 48 hours. A significant cohort effect indicates a between-cohort (control vs. intervention) difference in time until the first lactate order after mNEWS ≥7 and time until ICU transfer after mNEWS ≥7.

Multilevel logistic regression with patients nested within hospital floors (SAS PROC GLIMMIX) was used to examine a cohort as a predictor of each primary and secondary outcome as follows: lactate ordered within 24 hours of mNEWS ≥7 (yes/no), ICU transfer within 48 hours of mNEWS ≥7 (yes/no), and in-hospital mortality (yes/no). Multilevel linear regression with patients nested within hospital floors (SAS PROC MIXED) was used to examine cohort as a predictor of each continuous secondary outcome as follows: ICU LOS (in days) and hospital LOS (in days).

We then examined whether differences between cohorts in secondary outcomes varied based on whether a lactate was ordered. For each outcome, the following two models were conducted: one that contained the main effects of each cohort and a lactate order and a second one that contained both main effects as well as the interaction between a cohort and lactate order. Multilevel logistic regression models examined in-hospital mortality, and multilevel linear regression models examined ICU and hospital LOS. For all three outcomes, significant interactions were followed up by slopes analyses to examine the effect of a cohort separately among those who did and did not have a lactate order. SAS version 9.4 was used for all statistical analyses (SAS Institute Inc, Cary, NC).

Results

Table 1 reports the characteristics of patients who experienced an mNEWS of ≥7 stratified by cohorts. There were no significant differences in age, gender,

mNEWS value, and CCI scores by cohorts. Relative to the control cohort, patients in the intervention cohort were less likely to have had an ICU stay before experiencing an mNEWS of ≥7 (26.71% vs. 23.60%, $p = .04$).

Table 2 displays primary and secondary outcomes by cohorts. Discrete-time Cox regression analyses revealed a significant difference between cohorts in the time to the first lactate order, $\chi^2(1) = 106.56$, $p < .0001$. Those in the intervention cohort had a 138% increase in the hazard rate (accumulated risk of lactate ordering) compared with those in the control cohort (hazard ratio = 2.381). Furthermore, patients in the intervention cohort were approximately 2.5 times more likely to have a lactate ordered compared with the control cohort (odds ratio [OR] = 2.69, 95% confidence intervals [CIs] = 2.24–3.24, $p = .001$). Intervention and control cohorts did not significantly differ in whether patients were transferred to the ICU, time to ICU transfer, in-hospital mortality, ICU

Table 1. Characteristics of Patients With an Elevated Modified National Early Warning Score (mNEWS)[a] by Study Cohorts

Characteristics	Control cohort (*N* = 1741)	Intervention cohort (*N* = 1,610)	*p*
Age in yrs, mean (*SD*)[b]	63.43 (16.40)	62.74 (16.50)	.23
Age category, *N* (%)			.39[c]
Younger than 25 yrs	52 (2.99%)	46 (2.86%)	
25–34 yrs	78 (4.49%)	76 (4.73%)	
35–44 yrs	93 (5.35%)	113 (7.03%)	
45–54 yrs	217 (12.49%)	195 (12.13%)	
55–64 yrs	430 (24.74%)	398 (24.77%)	
65–74 yrs	442 (25.43%)	416 (25.89%)	
75 yrs and older	426 (24.51%)	363 (22.59%)	
Gender, *N* (%)			
Females	847 (48.65%)	768 (47.70%)	.58
Males	894 (51.35%)	842 (52.30%)	
Highest mNEWS value, *N* (%)			.28
7	1,184 (68.01%)	1,131 (70.25%)	
8	379 (21.77%)	335 (20.81%)	
9	120 (6.89%)	104 (6.46%)	
10	32 (1.84%)	24 (1.49%)	
11	21 (1.21%)	9 (0.56%)	
12+	5 (0.29%)	7 (0.43%)	
Previous ICU stay, *N* (%)	465 (26.71%)	380 (23.60%)	.04
Charlson Comorbidity Index, mean (*SD*)	1.59 (1.91)	1.66 (1.93)	.27

[a] An mNEWS at or above seven is a trigger for evaluation for clinical decompensation.
[b] Age was reported by $n = 1738$ and $n = 1,607$ in the control and intervention cohorts, respectively.
[c] Comparison of younger than 65 years to greater than or equal to 65 years.
ICU = intensive care unit.

Table 2. Primary and Secondary Outcomes by Study Cohorts and Examination of Between-Cohort Differences in Each Outcome

Outcome	Control cohort ($N = 1741$)	Intervention cohort ($N = 1,610$)	Effect of cohort (control = 0, intervention = 1)		
			χ^2	p	Hazard ratio
Primary outcomes					
Time to first lactate order (within 24 hrs) after mNEWS ≥7, hrs, mean (*SD*)	9.43 (7.29)	8.27 (6.99)	106.56	<.0001	2.381
Time to ICU transfer (within 48 hrs) after mNEWS ≥7, hrs, mean (*SD*)	22.15 (13.02)	22.62 (12.47)	0.43	.51	1.079
Outcome	**Control cohort ($N = 1741$)**	**Intervention cohort ($N = 1,610$)**	**Effect of cohort (control = 0, intervention = 1)**		
			F	***p***	**Odds ratio (95% CIs)**
Primary outcomes					
Lactate order within 24 hrs of mNEWS ≥7, N (%)	212 (12.18%)	428 (26.58%)	111.9	<.001	2.69 (2.24–3.24)
ICU transfer within 48 hrs of mNEWS ≥7, *N* (%)	148 (8.50%)	148 (9.19%)	0.48	.490	1.09 n (0.86–1.38)
Secondary outcomes					
In-hospital mortality, *N* (%)	73 (4.19%)	75 (4.66%)	0.49	.48	1.13 (0.81–1.57)
ICU length of stay, days, mean (*SD*)[b]	5.41 (8.98)	4.32 (7.03)	0.94	.33	NA[a]
Hospital length of stay, days, mean (*SD*)	11.69 (12.42)	11.14 (11.71)	0.24	.63	NA[a]

[a] Odds ratios are not applicable for continuous outcomes.
[b] $N = 148$ in each cohort transferred to ICU after an mNEWS of seven or greater, within 48 hours.
CI = confidence interval; ICU = intensive care unit; mNEWS = modified national early warning score.

LOS, or hospital LOS (all $p > .05$). Results remained the same in parallel models that controlled for a previous ICU stay.

Table 3 examines in-hospital mortality, ICU LOS, and hospital LOS as a function of cohorts, whether a lactate was ordered, and their interaction. There was a significant interaction between a cohort and whether a lactate was ordered predicting in-hospital mortality ($p = .013$). When a lactate was ordered in the first 24 hours after mNEWS ≥7, those in the intervention cohort were 47% less likely to have in-hospital mortality (OR = 0.53, 95% CIs = 0.31–0.90, $p = .02$), relative to those in the control cohort. Conversely, when a lactate was not ordered, there was no difference between cohorts in in-hospital mortality (OR = 1.25, 95% CIs = 0.81–1.93, $p = .32$). Similarly, there was a significant interaction between a cohort and whether a lactate was ordered predicting hospital LOS ($p = .0002$). When a lactate was ordered in the first 24 hours after mNEWS ≥7, the intervention cohort had a hospital LOS 4.70 days less than those in the control cohort (b = −4.70,

Table 3. Secondary Outcomes by Cohorts, Whether a Lactate was Ordered, and the Cohort by Lactate-Ordered Interaction

	In-hospital mortality		ICU LOS		Hospital LOS	
	OR (95% CI)	*p*	b (SE)	*p*	b (SE)	*p*
Main effects model						
Cohort (control = 0, intervention = 1)	0.89 (0.63–1.26)	.510	−0.98 (0.94)	.300	−1.23 (0.41)	.003
Lactate order within 24 hrs of mNEWS ≥7 (no = 0, yes = 1)	3.34 (2.36–4.75)	<.001	0.66 (0.97)	.510	6.93 (0.51)	<.001
Interaction model						
Cohort × lactate order	2.37 (1.20–4.69)	.013	3.47 (1.89)	.070	3.89 (1.06)	<.001

CI = confidence interval; ICU = intensive care unit; LOS = length of stay; mNEWS = modified national early warning score.

SE = 1.37, $p = .0007$). Figure 1 illustrates these two significant interactions. Conversely, when a lactate was not ordered, there was no difference between cohorts in hospital LOS (b = −0.66, SE = 0.38, $p = .08$). There was not a significant interaction between a cohort and whether a lactate was ordered predicting ICU LOS ($p = .07$).

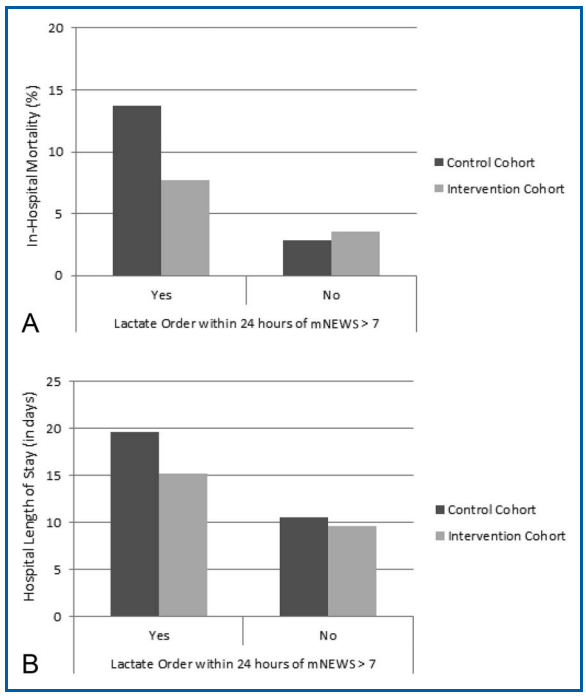

Figure 1. In-hospital mortality (%) (A) and in-hospital length of stay (B) by cohorts and whether a lactate was drawn. mNEWS = modified national early warning score.

Limitations

The pre–post design without randomization limits the capacity to make causal inferences and significant claims on the external validity of our results. However, we were able to match the populations by secular months, and there were few differences among the overall patient characteristics between cohorts. The design of this project did not allow us to determine the workload on the RRT by cohorts. As with all single-site, pre–post quality improvement studies, the presence of parallel quality improvement activities, such as code blue improvement and hospital LOS improvement, may serve as confounding variables. Checking lactic acid was required during the intervention period, which could have diluted the pool of decompensating patients for whom lactic acid was ordered. Another limitation was the need to modify the NEWS trigger component of the intervention from the validated NEWS standard because of difficulties obtaining a standard nursing neurologic status evaluation in the EMR to incorporate in the cloud software computations.[13] This is a practical problem that is likely to be encountered by other hospitals wanting to use a similar early warning score. We have subsequently resolved this challenge and are now using the standardized NEWS trigger, which is not reflected in this study.

Discussion

This quality improvement study evaluated if continuous cloud-based electronic monitoring coupled with a standardized RRT process could reduce the time to identification of and intervention on

clinically decompensating patients. For this study, recognition and early intervention of decompensation was determined by the clinical markers of time to lactate being ordered and time to transfer to the ICU after an mNEWS trigger (i.e., a score of seven or greater). Relative to controls, those who were part of the quality improvement intervention did show a reduction in the time to the first lactate being ordered but did not show a reduction in time to ICU transfer. Furthermore, there was no significant difference in the secondary outcomes of in-hospital mortality, ICU LOS, and hospital LOS between the intervention and control cohorts.

As part of the quality improvement process, the RRT evaluated any patient experiencing an mNEWS trigger from the cloud monitoring system. If the RRT confirmed an mNEWS of at least 5, then a lactate was ordered. Previous research indicates that delays in assessing lactate levels are associated with worse outcomes.[4,15] Therefore, we conducted exploratory analyses to determine if the intervention showed better outcomes relative to controls, especially among those with a lactate order. Among patients experiencing an mNEWS trigger who also had a lactate ordered within 24 hours, those in the intervention cohort spent 4.7 fewer days in this hospital and had 47% lower in-hospital mortality than those in the control cohort. Checking lactic acid during the control period was performed based on a clinician preference but was required during the intervention period for any patient with persistently elevated mNEWS after RRT evaluation. This requirement may have diluted the pool of potentially decompensating patients for whom lactic acid was ordered; however, there was no difference in outcomes between intervention and control cohorts among those experiencing an mNEWS trigger who did not have a lactate ordered. We attribute this improvement in outcomes not to the slight reduction in time to lactate but the structured process of evaluation and intervention provided to these patients because they were identified as decompensating, often at an earlier time. These findings provide preliminary evidence for coupling cloud-based vital sign monitoring with timely assessment and intervention on the hospital ward by experienced RRTs of clinically decompensating patients, especially those with suspected sepsis. The null findings associated with early ICU transfer suggest that some decompensating patients were evaluated and then managed on the acute care ward without ICU transfer. This finding may also reflect the low-positive predictive value of NEWS triggers described previously in the literature.[11]

For this study, the chosen mNEWS trigger for initiating RRT evaluation was mNEWS $\geq$7. This score was selected based on internal data showing patients' highest mNEWS that most often resulted in ICU transfer. To detect decompensating patients earlier, the RRT would ideally evaluate all patients with mNEWS $\geq$5.[12] However, the resultant workload would have been too large for the RRTs to handle at our hospital. To evaluate all patients with mNEWS $\geq$7, the hospital increased staffing of RRT nurses by one nurse per shift to handle the increased workload. Using the mNEWS $\geq$7 trigger, the RRT nurses saw four extra patients per hospital shift, which resulted in detection and transfer of one patient to the ICU every 2.6 shifts. RRT nurses did note that on re-evaluation of vital signs the mNEWS would not be $\geq$7 on some patients (false positive), and they provided many interventions in conjunction with the treating physician to keep them on the floor. Furthermore, these interventions did not lead to a detectable change in hospital LOS or mortality in this study. Beyond this intervention, the RRT nurses do have other responsibilities within the hospital; however, the increased workload and cost associated is pertinent to any hospital hoping to implement similar processes.[6,7]

Conclusions

The results of this study provide some preliminary evidence for a pragmatic integration of cloud-based, automated monitoring with standardized and timely intervention by RRTs. This process is being continued at our institution, based on the experience and findings of this study, with the next steps focused on improving compliance with indicated interventions.

Implications

Patients with serious illnesses requiring hospital admission are always at a risk for clinical decompensation. Improving the monitoring processes for admitted patients, especially those outside of the ICU, is an important safety outcome that can impact patient morbidity and mortality. Early detection of decompensation on acute care floors and within the emergency department coupled with timely and appropriate interventions is an important quality and safety goal. The vast amount of data readily available within electronic records can be overwhelming and difficult for individual humans to process. Using advanced computational methods to

automate data processing to create more accurate screening algorithms will be vital for further improving early warning systems. The ideal system would detect an individual's decompensation at early stages in a highly sensitive manner (with potentially fewer false positives) and could direct timely assessment by the appropriate clinical personnel.

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