Utilization of Deterioration Index Model to Improve Sepsis Management in Medical Unit

Phudorji L Sherpa BSN, RN, CCRN

Under Supervision of

Dr. Bridgitte Gourley

Second Reader

Dr. Lynn Marie Bullock

A DNP Project Manuscript
Submitted in Partial Fulfillment of the Requirements for the
Doctor of Nursing Practice Degree

School of Nursing, University of Maryland at Shady Grove
May 2022

Abstract

Problem and Purpose: One third of inpatient deaths are related to sepsis. In a medical unit, a sample of 245 sepsis patients in 2020, 28.4 % failed timely sepsis treatment and 35.4% lacked blood culture within 3 hours sepsis recognition. The implementation site was a 35-bed adult medical unit where the utilization of the existing sepsis best practice alert (BPA) in the EHR was substandard. From November 2020 to February 2021, unit nurses bypassed or ignored 84% of sepsis BPA. This DNP project sought to improve recognition of early sepsis complications and management in a medical unit by implementing a new EPIC BPA Deterioration Index with Sepsis Score (DISS) and sepsis bundle.

Methods: Based on Press Ganey Sepsis Workflow, nursing staff in the unit were provided education and training on sepsis, sepsis bundle, and early identification and management of sepsis. Nurses were also provided training on DISS, which was incorporated into the hospital EPIC system. Measurements included DI BPA encounters, length of stay (LOS), and Blood culture draw compliance. The intervention site was a 35-bed adult medical unit.

Results: Blood Cultures in <3 hours improved an average of 30% for the intervention period, and the average monthly length of stay trended down during the intervention. The number of alerts decreased significantly during the intervention period.

Conclusion: Machine learning prediction models such as DISS with sepsis bundle can be utilized to identify early sepsis complications and improve timely blood culture compliance, and may lower LOS for patients with sepsis.

Utilization of Deterioration Index Model to Improve Sepsis Management in Medical Unit

According to the World Health Organization (WHO), sepsis is defined as a complex dysregulated host response to infection; if not recognized early and managed promptly, it can lead to shock, multiple organ failure, and death (WHO, 2020). The Centers for Disease Control and Prevention (CDC) reports that approximately 1.7 million adults develop sepsis in the United States each year, and 1 in 3 inpatient deaths is related to sepsis (CDC, 2021). Maryland's death rate from sepsis was 12.5, above the national average of 10.6 per 100,000 in 2017 (CDC, 2018). In this teaching hospital, there were 17 deaths out of 1015 patients diagnosed with sepsis between January 2019 and August 2021.

There were 669 patients with sepsis in the project hospital in the last two quarters of 2020. In a random sampling of 245 sepsis patients in these two quarters, 28.4 % of patients failed treatment as per the sepsis algorithm based on Press Ganey Sepsis Workflow (Press Ganey Associates, 2021). Not drawing blood cultures (35.43%) within 3 hours of sepsis recognition was one of the main reasons for failure in following sepsis core measures outlined by the Centers for Medicare and Medicaid Services (CMS, 2021). While these were random samples and did not account for all sepsis patients, the trend was concerning. Additionally, the utilization of the sepsis BPA was substandard. From November 2020 to February 2021, more than 84% of sepsis BPA were bypassed or ignored by nurses in a 35-bed medicine unit, the DNP project site. The majority of nurses in the unit are inexperienced with less than five years in nursing, lack adequate knowledge and skills to recognize sepsis. Ignoring sepsis alerts can put patients at significant risk of quick health deterioration.

This quality improvement (QI) project aimed to improve recognition of early sepsis complications and management in a medical unit by implementing DISS and sepsis bundle.

Literature Review and Synthesis

The Surviving Sepsis Campaign, introduced in 2004, was in response to the prevalence of sepsis. There have been several screening tools and algorithms for the detection of sepsis. Many hospitals still use one of several sepsis screenings tools and algorithms, such as the Systemic Inflammatory Response Syndrome (SIRS) criteria, the quick sepsis-related organ failure assessment (qSOFA) score, and the modified early warning system (MEWS). In recent years, machine learning prediction models (MLPM) have shown promising results to identify and predict sepsis early and help decrease the length of stay (LOS) for patients diagnosed with sepsis.

In a meta-analysis, Islam et al. (2019) found that the MLPM performed better than the existing sepsis scoring systems such as SIRS, MEWS, SOFA, and qSOFA for identifying and predicting sepsis patients three to hours before the onset. However, this meta-analysis included only seven studies. They evaluated different MLPM types for identifying sepsis rather than focusing on a few specific models. Nevertheless, all the MLPM types performed better than the traditional methods of sepsis in the identification and prediction of sepsis. In their systematic review and meta-analysis of 28 studies, Fleuron et al. (2020) showed high sensitivity of individual MLPM to predict sepsis earlier in hospitals accurately.

In a systematic review of the use of patient monitoring systems (PMS) to improve sepsis recognition and outcomes, which included four systematic reviews and 15 individual studies comprising randomized controlled trials, quasi-experimental studies, and observational studies, four studies found a significant effect of the sepsis PMS on LOS (Gale & Hall, 2020). Additionally, in a prospective study that evaluated 75,147 patient encounters from early 2017 to mid-2018, there was a 32.3% reduction in hospital LOS and a 22.7% reduction in 30-day readmission rate for sepsis-related patient stays when using the machine learning algorithms in clinical outcomes analysis (Burdick et al., 2020). In evaluating whether a PMS improves sepsis care processes such as the CMS core measures, several studies showed that PMS significantly improved the time to administration of antibiotics, lactate draw, blood culture draw, and fluid administration (Gale & Hall, 2020).

Early recognition of sepsis complications needs prompt intervention. Quality improvement programs are associated with increased adherence to resuscitation and management of sepsis bundles and reduced patient mortality from sepsis complications (Damiani et al., 2015). Educational programs can improve the nursing staff's knowledge, confidence, and competence in using the new early warning system (Jensen et al., 2018; Saab et al., 2017). In a sepsis educational program targeting 87 nurses working in critical care and emergency department settings, the multimodal sepsis educational program helped nurses acquire sepsis knowledge and begin early goal-directed sepsis therapy (Delany et al., 2015). However, this study was done in critical care and emergency department settings.

Most of the studies included in this manuscript were systematic reviews with meta-analyses of prospective studies, RCTs, and cohort studies and were given ratings of (I) or (IV) for the level of evidence (Melnyk & Fineout-Overholt, 2019). The quality rating for the research evidence offered in the studies was between A and C (Newhouse, 2006). A detailed evidence review table is available in Appendix A and B.

Theoretical Framework

The right theories and framework selection helps provide effective support for leading change in the healthcare environment. Kotter's Eight-Step Process for Leading Change Model provides a framework for guiding change (Kotter, 1996). The three tenets of the theory and its eight steps help address the urgency of the problem statement. Kotter's model was selected for the project because it was easy to understand and apply in a healthcare environment. The theory offered adaptability when inadequacies or failures were identified with the proposed change and allowed for the incorporation of staff nurses' feedback. Theory's eight steps, such as forming a guiding change team, communication and planning with stakeholders, acknowledging short-term wins, building change, and sustaining change, were similar proposed steps in the QI project.

Helfrich et al. (2007) framework provided detailed steps to improve an organizational innovation implementation plan. The goal of improving early sepsis recognition and management was consistent with this hospital's values and priorities. Central to this goal was the optimum utilization of the sepsis screening tool. DISS is a type of MLPM, which helps identify whether a patient's deterioration in health status is due to sepsis. The tool's ability in predicting early patient health deterioration to sepsis compared to other sepsis screening tools was central to the need of the implementation climate. Since most nurses were inexperienced in the DNP project site, the nursing executive leadership and the hospital educational department supported the idea of training nurses on sepsis recognition and management. Identification of hospital and unit champions to promote utilization of DISS and provision of adequate resources in the preparation of educational materials were other essential factors for a robust implementation climate.

Methods

This QI project occurred in a 35-bed adult medicine unit. A diverse population of patients over 18 years of age are admitted to the unit with infectious processes, acute or chronic heart or lung conditions, uncontrolled metabolic conditions, and other disorders. The selected patients were either diagnosed with sepsis during admission or inpatient stay.

Deterioration Index (DI) BPA with accompanying sepsis score (DISS), was made to fire after composite scores for DI BPA reached the established threshold of 60 and above. DISS score is generated based on an algorithm developed by Epic Systems. Various predictors in this algorithm include the patient's age, vital sign measurements, nursing assessments, and laboratory values of hematocrit, white blood cell count, potassium, sodium, blood pH, platelet count, and blood urea nitrogen. The hospital informatics department incorporated DISS in the electronic health record (EHR) after many weeks of inputs from the hospital's sepsis workgroup, of which the DNP student was an integral part. This BPA was implemented in hospital Epic on September 27, 2022.

Sepsis educational training via an interactive e-learning platform called Captivate in the hospital's HealthStream site was utilized to explain sepsis, DISS, sepsis bundle, and ways to recognize and manage early sepsis identification based on Press Ganey Sepsis Workflow (Press Ganey Associates, 2021). The online training contained five knowledge-based questionaries embedded in the training. Nurses were highly encouraged to complete the training, but it was not mandatory.

Training compliance was obtained from the IT department, and non-compliant nurses were notified through e-mail. Similarly, during Nursing Bootcamp, face-to-face training was provided for new nurses and also during unit rounds for floor nurses. Nursing Bootcamp is a collection of courses that give nurses opportunities to master critical nursing skills and knowledge. Sepsis badge cards with recommendations for the DISS alert and sepsis bundles were distributed to unit nurses. There were consistent reminders to utilize DISS alerts during morning nurse huddles, unit rounds, and e-mail communications from the unit leadership and charge nurse group, and the DNP student.

DISS as a sepsis screening tool and nurses' response and blood culture draw within three hours of sepsis recognition were used as process measures. Data for these measures were obtained from the patient portal in EPIC and the DNP dashboard in the hospital data bay. As for the outcome measure, which measured the LOS for sepsis patients, the hospital data bay was utilized to monitor the length of stay. Patients and nurses were deidentified using unique codes for data confidentiality. The DNP dashboard in the data bay was only accessible by two DNP students.

Results

Sepsis educational training via an interactive e-learning platform Captivate in the hospital's HealthStream site and face-to-face training in the unit and during new nurses' boot camp proved effective, with 91.4% completing the training. The training enabled nurses to learn about sepsis, DISS, and accompanying sepsis bundle and how to recognize and manage early sepsis identification based on Press Ganey Sepsis Workflow.

Sepsis training and EHR process improvement such as DISS with accompanying sepsis bundle led to improved blood culture draw with timely blood culture post-DI BPA alert being 81.80%. Overall, the percentage of blood cultures drawn within three hours of diagnosis of sepsis improved by 30% during the intervention period. Compared to the baseline 57.8% timely blood culture draw, the intervention three months recorded 78.5%, 84.6%, and 63.1% respectively for blood cultures drawn within three hours of sepsis diagnosis.

The number of DI BPA encounters significantly decreased by 20%, 70%, and 50% during the intervention months of October, November, and December, respectively, when the DI BPA composite threshold scores were increased from 50 to 60 at the end of September 27, 2021. Compared to the old Sepsis BPA that was discontinued before the beginning of the project, the number of BPA alerts had significantly gone down by 98.6% compared to the highest monthly recorded sepsis BPA alerts from the previous year. The reliability of DI BPA to fire appropriately ranged from 85% to 92%. It fired inappropriately intermittently (15.40%) and did not fire at all when it should have fired for a DI score > 60 (8.1%).

Compared to baseline LOS of 11.21 days, the average LOS for the intervention period was 12.43 days, which is likely skewed due to 2 extended stays of 48-52 days and several patients with LOS >30 days. However, a downward trend was seen with monthly LOS of 12.4, 12.2, and 10.6 days respectively, during the intervention months. Detailed results are available in Appendix C.

Limitations: Some of the limitations of this DNP project include limited number of patients and reach: this sepsis educational initiative took place in one unit rather than in the entire hospital and only involved 81 septic patients. Sepsis Narrator, which was supposed to be the primary intervention for this project, was not implemented due to resource allocation of IT personnel during the Covid surge. The informatics specialists could not build the sepsis narrator on time for our project. The sepsis narrator would have included sepsis predictive model score, sepsis huddle time, sepsis timer, and outstanding interventions based on Press Ganey Sepsis Workflow.

Discussion

An interactive e-learning platform and face-to-face training can be an effective educational initiative to learn about sepsis, MLPM, sepsis bundle, and how to recognize and manage early sepsis identification. Educational programs in other studies have improved the nursing staff's knowledge, confidence, and competence in using the new early warning system (Jensen et al., 2018; Saab et al., 2017). Similarly, multimodal sepsis educational programs helped nurses acquire sepsis knowledge and begin early goal-directed sepsis therapy (Delany et al., 2015). However, the sepsis and DISS training completion was not robust initially. While there were nurses who embraced the new improved BPA and completed training instantly, many nurses had to be reminded on multiple occasions to complete the training. There was also some resistance to adoption or excitement among some nurses for this new BPA. Despite the completion of the training, some nurses still doubted the efficacy of DISS. It did not help that despite the high reliability (85-92%) of DI BPA to fire appropriately, it was not perfect, firing inappropriately intermittently or not firing at all when it should have. Everett Rogers had defined how diffusion of innovations work and had classified different categories of adopters for innovation in his seminal book Diffusion of Innovations (1962). However, a caveat to validate the above assessment should also be looked at from the perspective of nurses' fatigue for DNP projects, as there were three other projects simultaneously in this unit.

One of the prevailing concerns of nurses during the intervention period was that the BPA did not match patient status in that patient's condition did not look as concerning as the BPA indicated. The validity of this nursing assessment is well supported by our collected data, which showed that many sepsis patients with DI BPA initially did have low sepsis scores. However, approximately 70% of sepsis patients with DI BPA encounter who had an initial lower sepsis score of <10 eventually had a maximum sepsis score during their hospitalization, an indication of DISS to recognize early high-risk sepsis patients as reported in other studies (Singh et al., 2020). There are times when things are not always as they seem, and nurses would be wise to acknowledge the early scores and be vigilant.

Even though the Deterioration Index BPA has a sepsis score embedded in it, it is not a specific sepsis BPA; the DI BPA helps identify patients at risk for quick clinical deterioration from any medical conditions that requires higher level of care. Sepsis Narrator, which was supposed to be the primary intervention for this project, was not implemented due to resource allocation during the Covid surge. However, DISS and the sepsis bundle that was included in our project have many features that the proposed sepsis narrator shares and as the project demonstrated, can alert nurses to early decompensation.

This study supports the findings from other studies on the efficacy of machine learning prediction models in identifying and predicting sepsis patients prior to the onset of sepsis complications. When optimized based on institutional needs, the computer-based sepsis prediction model can be utilized to identify sepsis early and more accurately, findings supported in other meta-analysis studies (Islam et al., 2019; Fleuren et al., 2020).

Sepsis training and EHR process improvement lead to improved blood culture draw or increased adherence to sepsis core measures (Damiani et al., 2015; Jensen et al., 2018). Consistent with findings from other previous studies, our project reported improved blood culture compliance by 30%. Despite reporting down-trending LOS during the intervention period, it is not possible to correlate sepsis educational training and computer-learning-sepsis model implementation as a factor to improve LOS as there were several patients whose stay was more than 30 days. There were also several factors such as patient comorbidities, age, patient acuity at presentation that factor into LOS. Additional operational challenges including varying nurse-to-patient ratio due to increasing nursing shortage, the unit being designated as a Covid unit, and Covid resurgence had impacts on the unit and may have also affected LOS.

Conclusion

The implementation of Deterioration Index BPA with sepsis score and accompanying sepsis bundle can be utilized to identify early sepsis complications and offer prompt management in a medical unit. DI BPA can help recognize high risk sepsis patients earlier. Blood Cultures drawn in <3 hours improved on average 30% over course of intervention. Average LOS trended down later in project. Reduced number of BPA alerts may have contributed to higher quality responses. The hospital sepsis workgroup is launching a hospital-wide Sepsis Narrator. The narrator has several components that were utilized in this project, was built based upon best evidence identified in the literature review for this project and more importantly, the sepsis workgroup has had the benefit of this project for inputs and recommendations. The primary goal of the Surviving Sepsis Campaign, the Centers for Disease Control and Prevention, the World Health Organization, and this hospital include early detection of sepsis and prompt medical management to reduce mortality related to sepsis, and this DNP project supported that goal.

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Singh, K., Valley, T. S., Tang, S., Li, B. Y., Kamran, F., Sjoding, M. W., Wiens, J., Otles, E., Donnelly, J. P., Wei, M. Y., McBride, J. P., Cao, J., Penoza, C., Ayanian, J. Z., & Nallamothu, B. K. (2021). Evaluating a Widely Implemented Proprietary Deterioration Index Model among Hospitalized Patients with COVID-19. Annals of the American Thoracic Society, 18(7), 1129–1137. https://doi.org/10.1513/AnnalsATS.202006-698OC

Appendix A

Table 1

Evidence Review Table

Citation: Islam, M. M., Nasrin, T., Walther, B. A., Wu, C. C., Yang, H. C., & Li, Y. C. (2019). Prediction of sepsis patients using machine learning approach: A meta-analysis. Computer Methods and Programs in Biomedicine, 170, 1–9. https://doi.org/10.1016/j.cmpb.2018.12.027					Level (Melnyk) I
Purpose/ Hypothesis	Design	Sample	Intervention	Outcomes	Results
To conduct a meta-analysis to investigate the potential of machine learning for identifying sepsis patients.	Systematic Review with Meta-Analysis	**Search Strategy:** A search was conducted using various search engines PubMed, EMBASE, Google Scholar, Scopus were searched between January 1, 2000, and March,1, 2018 to find out relevant studies. Some of the MeSH terms used to search the articles were: "Machine learning, machine learning model, machine learning algorithms, artificial intelligence, sepsis prediction. Two authors independently extracted study data and assessed it. The chief investigator resolved disagreements between the authors. # **Eligible**: 135 references were initially identified. After duplicates removal, and records screened, only 14 were deemed eligible based on eligibility criteria.	**Control**: Patients who were diagnosed sepsis with in-hospital sepsis criteria with SIRS, MEWS, and SOFA, **Intervention**: Machine learning performance to predict sepsis **Intervention Protocol**: Not applicable to SR critique. Note: SIRS = Systemic inflammatory response syndrome, MEWS = Modified early warning system, SOFA = Sequential organ failure assessment, q SOFA = Quick Sequential organ failure	**Dependent Variable/s (primary)**: • Sepsis prediction 3 to 4 h prior to onset • Sepsis detection (0 h) **Secondary**: None **Measure**: SIRS criteria are defined as: 1. Heart rate > 90 beats/ min, 2. body temperature > 38 °C or < 36 °C, 3. respiratory rate > 20 breaths/min 4. white blood cell count > 12,000 cells/µL or < 4,000 cells/µL. Organ dysfunction criteria are defined as: 1. Lactate > 2 mmol/L 2. Systolic blood pressure < 90 mmHg 3. Urine output < 0.5 mL/kg, over two hours 4.	**Statistical Procedures(s):** The sensitivity, specificity, and receiving operating curve (ROC) value with 95% confidence interval (CI) was utilized for predicting sepsis patients. MetaDiSc (version 1.4) was used for pooled estimate of AUROC, sensitivity, specificity and diagnostic odds ratio. An I^2 value was used to assess the statistical heterogeneity **Results**: For machine learning models, the pooled area under receiving operating curve (SAUROC) for predicting sepsis onset 3 to 4 h before, was 0.89 (95%CI: 0.86–

		# **Accepted**: Seven articles met the inclusion criteria. # **Excluded:** Six articles were excluded for unclear outcome, ineligible method, full-text duplication. **PRISMA**: The study flow diagram was provided with inclusion and exclusion details. **Power Analysis**: Not applicable to SR critique.		Creatinine > 2 mg/dL 5. Bilirubin > 2 mg/dL 6. Platelet count < 100,000 μL 7. International normalized ratio > 1.5 8. PaO2 > 0.5. InSight, a machine learning classification system, which uses multivariable combinations of easily accessible patient data (vitals, peripheral capillary oxygen saturation, Glasgow Coma Score, and age). Included studies compared InSight predictions for three most common patient deterioration scoring systems: SIRS, SOFA and MEWS. APeX, developed by Epic Systems, was some of the other machine learning system. Only three studies provided results of external validation	0.92); sensitivity 0.81 (95%CI:0.80–0.81), and specificity 0.72 (95%CI:0.72–0.72) whereas the pooled SAUROC for SIRS, MEWS, and SOFA was 0.70, 0.50, and 0.78. Additionally, diagnostic odd ratio for machine learning, SIRS, MEWS, and SOFA was 15.17 (95%CI: 9.51–24.20), 3.23 (95%CI: 1.52–6.87), 31.99 (95% CI: 1.54–666.74), and 3.75(95%CI: 2.06–6.83). **Conclusion**: The machine learning approach performed better than the existing sepsis scoring systems in predicting sepsis. **SR Bias Risk:** The risk of bias in included studies was low.

Citation: Singh, K., Valley, T. S., Tang, S., Li, B. Y., Kamran, F., Sjoding, M. W., Wiens, J., Otles, E., Donnelly, J. P., Wei, M. Y., McBride, J. P., Cao, J., Penoza, C., Ayanian, J. Z., & Nallamothu, B. K. (2021). Evaluating a Widely Implemented Proprietary Deterioration Index Model among Hospitalized Patients with COVID-19. Annals of the American Thoracic Society, 18(7), 1129–1137. https://doi.org/10.1513/AnnalsATS.202006-698OC					Level IV
Purpose/ Hypothesis	Design	Sample	Intervention	Outcomes	Results
To independently evaluate the Epic Deterioration Index (EDI) in hospitalized patients with COVID-19 overall and in disproportionately affected subgroups.	Cohort study	**Sampling Technique**: Convenience Sampling: Adults 18 years and older diagnosed with COVID-19 who were admitted to Michigan Medicine (i.e., the academic health system of the University of Michigan in Ann Arbor) between March 9, 2020, and May 20, 2020, from the emergency department, outpatient clinics, and outside hospital transfers. **Eligible** # Not provided **Exclusion** # 286 which included patients who were admitted directly to an intensive care unit (ICU) (n = 215), discharged to home or a separate facility on hospice (n = 34), where EDI scores were not available (n = 10), and patients who did not experience the composite outcome (n = 27). **Inclusion** # 392 hospitalizations for 369 patients with COVID-19; Two patients had three hospitalizations and 19	**Control**: All hospitalized patients at Michigan Medicine **Intervention**: COVID-19 patients admitted to Michigan Medicine **Protocol or Intervention Fidelity**: Calculations of the EDI begin immediately after hospital admission and then continue at regular 15-minute intervals until discharge. The EDI is based on algorithm with several predictors relevant to patients with COVID-19, including age, vital sign measurements (systolic blood pressure, temperature, pulse, respiratory rate, oxygen saturation), nursing assessments (Glasgow Coma Scale, neurological assessment, cardiac rhythm, oxygen requirement), and laboratory values	**Dependent Variables:** A composite of adverse outcomes that included the first of any of the following events that occurred during the hospitalization: ICU-level care, mechanical ventilation, or in-hospital death **Measure**: Of all hospitalizations, patients resulting in ICU-level care, requiring mechanical ventilation, and who died during hospitalization were obtained from patient hospitalization records. The proposed EDI thresholds of one institution might not be applicable in other institutions, affecting generalizability in other settings.	**Statistical Procedures(s):** Calculation of empirical 95% confidence intervals (95% CIs) for the AUC using 1,000 bootstrap replicates of the study cohort. **Results**: 103 (26%) met the composite outcome. The area under the receiver-operating characteristic curve of the EDI was 0.79 (95% confidence interval, 0.74–0.84). Patients who met or exceeded an EDI of 68.8 made up 14% of the study cohort and had a 74% probability of experiencing the composite outcome during their hospitalization with a sensitivity of 39% and a median lead time of 24 hours from when this threshold was first exceeded. Patients who did not experience the

		patients had two hospitalizations. **Power Analysis**: Not performed. **Group Homogeneity**: Homogeneity information was provided in Table 1, the mean patient age was 64 years, 43% were women, and 43% were Black. The composite adverse outcome occurred in 103 (26%) out of the 392 hospitalizations with a median length of follow-up of 5.3 days, and the outcome occurred at a median of 2.5 days after admission. In terms of comorbidities, 75% had hypertension, 48% had cardiac arrhythmias, 42% had diabetes, and obesity.	(hematocrit, white blood cell count, potassium, sodium, blood pH, platelet count, blood urea nitrogen). The EDI is calculated every 15 minutes, and if a patient crossed a given alerting threshold even once, this would bring the patient to the clinician's attention is linked to an alert. The scores from the EDI calculated every 15 minutes throughout the hospitalization to predict the composite adverse outcome during the hospitalization. The physicians were blinded to EDI score.		composite outcome within 48 hours, 14 (13%), never exceeded an EDI of 37.9, with a negative predictive value of 90% and a sensitivity above this threshold of 91%. **Conclusion**: The EDI effectively recognizes a small group of high-risk and low-risk patients with COVID-19, but it has low sensitivity as an early warning system for high-risk patients with COVID within 24 hours, but for patients with a low composite score within 48 hours, it had high sensitivity and negative predictive value.
Citation: Damiani, E., Donati, A., Serafini, G., Rinaldi, L., Adrario, E., Pelaia, P., Busani, S., & Girardis, M. (2015). Effect of performance improvement programs on compliance with sepsis bundles and mortality: a systematic review and meta-analysis of observational studies. PloS One, 10(5), e0125827. https://doi.org/10.1371/journal.pone.0125827					Level I
Purpose/	Design	Sample	Intervention	Outcomes	Results

Hypothesis					
To perform a systematic review of studies evaluating the impact of performance improvement programs on compliance with Surviving Sepsis Campaign (SSC) guideline-based bundles and/or mortality.	A Systematic review and meta-analysis of observational studies	**Search Strategy**: Various search engines and databases such as Medline (PubMed) and others were utilized with keywords “sepsis,” “septic shock,” “bundle,” “guidelines,” “surviving sepsis campaign,” “implementation,” “compliance,” “performance improvement program,” “quality improvement program.” A total of 1559 studies were initially identified. The selection of studies included those which evaluated compliance to an individual or combined sepsis bundle targets and or mortality following the implementation of performance improvement programs. Interventions consisted of educational programs, process changes or both. Two independent reviewers screened all identified and assessed the selected full-text articles for eligibility. Disagreements were resolved through discussion. **Eligible** # 90 articles were eligible.	**Control**: adult patients with sepsis, severe sepsis, or septic shock who were treated before or without the influence of the implementation program **Intervention**: adult patients with sepsis, severe sepsis, or septic shock who were treated after the process improvement program to increase compliance to one or more components of the 6-hour or 24-hour sepsis bundles as based on the 2004 SSC guidelines **Intervention Protocol**: Not applicable to SR critique. Note: The performance improvement program could be educational only, process change only or both educational and process change.	**Dependent Variables**: Patient mortality and changes in compliance to individual and/or combined sepsis bundle targets after the performance improvement program **Measure**: Compliance measured by data on lactate measurement, antibiotics administration time, drawing of blood cultures, fluid resuscitation, CVP measurement, SvO2 measurements. Patient mortality measured by data on deaths/survival.	**Statistical Procedures(s)**: The odds ratio (OR) was chosen for the data synthesis. The DerSimonian and Laird random-effects model was utilized to assess variation, and forest plots were used to represent the results. Meta-regression and subgroup analyses were performed to assess the effect of study quality. **Results**: The overall estimate size indicated a statistically significant positive association between the quality improvement interventions and compliance with the 6-hour sepsis resuscitation bundle (OR = 4.12 [95% confidence interval 2.95–5.76], p <0.001. Most of the studies reported a significant increase in compliance with the 24-hour sepsis bundle following the implementation of the program, the combined OR was 2.57 [1.74–3.77] (p<0.001).

		Inclusion # 45 articles met the inclusion criteria. **Exclusion** # 45 articles were excluded for not having performance improvement, no sepsis, no control group, and publications in other languages and other reasons. **Power Analysis**: Not applicable to SR. **PRISMA**: Adheres to standards for reporting systematic review and meta-analysis studies .			These studies also showed a reduction in mortality (OR = 0.66 (0.61-0.72). **Conclusion**: There was an increased adherence to resuscitation and management sepsis bundles after performance improvement programs, and reduced mortality of patients with sepsis complications. **Bias**: Low Bias Risk based on the study process.
Citation: Thursky, K., Lingaratnam, S., Jayarajan, J., Haeusler, G. M., Teh, B., Tew, M., Venn, G., Hiong, A., Brown, C., Leung, V., Worth, L. J., Dalziel, K., & Slavin, M. A. (2018). Implementation of a whole of hospital sepsis clinical pathway in a cancer hospital: impact on sepsis management, outcomes and costs. BMJ Open Quality, 7(3), e000355. https://doi.org/10.1136/bmjoq-2018-000355					Level III
Purpose/ Hypothesis	Design	Sample	Intervention	Outcomes	Results
To develop and implement a hospital clinical pathway (SP) for the management of sepsis in a specialized cancer hospital and to measure the impact on patient outcomes and healthcare utilization.	Controlled before-and-after study	**Sampling Technique**: Convenience sampling. ICD-10 diagnosis codes and patients identified from the hospital-based electronic records system were utilized for patient selection for the SP cohort in a 100 inpatient bed tertiary cancer hospital **Eligible #** No information provided. **Exclusion #** no information provided.	**Control**: Patients not participating in sepsis pathway **Intervention**: Patients participating in Sepsis Pathway **Protocol or Intervention Fidelity**: A comprehensive hospital-wide education campaign accompanied the SP implementation. Members of the sepsis-working group delivered a standardized	**Dependent Variables**: Patient outcomes and sepsis management targets. **Measure**: Patient outcomes were measured via ICU admissions, 30-day all-cause mortality, hospitalization cost, whereas sepsis management target was measured by data on lactate measurement, appropriate antibiotics administration, time to	**Statistical Procedures(s) and Results**: a X2 test compared categorical variables, and a Mann-Whitney U test compared continuous non-parametric variables. A t-test compared mean differences for those on the SP versus the historical cohort. **Results**: After the implementation of the hospital-wide SP,

		Inclusion # 323 patients were included in pre-implementation and postimplementation evaluation. There were 111 patients in the historical cohort and 212 patients in the postimplementation cohort, with 176 patients on the Sepsis Pathway (SP) and 36 patients not on SP. **Power Analysis**: Not provided. **Group Homogeneity**: Homogenous sample except for the higher proportion of surgical oncology patients (22.7% vs. 11.7%) and patients having surgery within 30 days (18.3% vs. 6.3%) in the SP cohort (all p<0.05).	presentation to medical and nursing, and pharmacy staff in all clinical areas. Weekly email communications summarizing key sepsis management principles and real-time audit results were also distributed to all staff. A series of multichoice questions were emailed to all staff. Whenever a patient met the criteria for sepsis pathway, a physician would be notified immediately, and a nurse would start IVs and draw blood cultures and lactate. A physician would have to see the patient within 30 minutes for antibiotics and fluid orders and follow the pathway's algorithm.	antibiotics administration. The sepsis working group conducted weekly real-time audit results. Time to antibiotic initiation was the process measure that nursing staff preferred as the best performance measure in each clinical area. Interrater reliability and information on how the audit was conducted were not provided.	there was a significantly higher proportion of patients' lactate measurement, appropriate administration of the first antibiotic, shorter time to the first dose of antibiotics, lower rates of ICU admission of patients, lower ICU length of stay, and lower sepsis-related mortality and 30-day all-cause mortality (all p<0.05). **Conclusion**: There was a significant improvement in patient outcomes and reduced costs after the implementation of SP. This pathway has been successfully implemented in one another hospital in Victoria.

Citation: Delaney, M. M., Friedman, M. I., Dolansky, M. A., & Fitzpatrick, J. J. (2015). Impact of a sepsis educational program on nurse competence. Journal of Continuing Education in Nursing, 46(4), 179–186. https://doi.org/10.3928/00220124-20150320-03	Level III

Purpose/ Hypothesis	Design	Sample	Intervention	Outcomes	Results

To evaluate the impact or influence of a multimodal sepsis educational program for critical care and emergency department nurses on knowledge acquisition and self-assessed competence in the early recognition and treatment of patients with sepsis.	Quasi-experimental study	**Sampling**: Purposive convenience sampling. Nurses from critical care specialties and emergency departments were selected. **Eligible#** Not provided. At least a year-long training fellowship in critical care and emergency nursing was a prerequisite. **Exclusion** # Not provided **Inclusion** # 87 nurses working in critical care and emergency department. **Power Analysis:** Minimum to treat was 64 for an alpha significance of less than 0.05, a statistical beta power of 0.08. **Group Homogeneity**: Not homogenous. 87 RNs, of which 70 were women (80.5%) and 17 were men (19.5%). 96.3% of participating nurses had a baccalaureate degree in nursing. Only nurses from specialized units were selected: 65.9% worked in ICU, 29.3% in ED, 4.9% in PACU.	Pretest and posttest comparison of nurses after the Taming Sepsis Educational Program® (TSEP™) **Intervention Fidelity**: A specialized sepsis education program for nurses, TSEP™ was utilized as an interventional program. A pre-test assessed comprehension of sepsis, institute for healthcare improvement (IHI) IHI bundles, TeamSTEPPS teamwork and communication, health literacy, and cultural competency (HLCC). Nurses self-assessed competence surveys, using the Nurse Competence Scale (NCS), were completed online. NCS also had three additional sepsis-specific statements added to it. Each participant had a unique identification code. Qualtrics program was utilized to gather NCS survey and a researcher obtained the data from Qualitrics. The NCS surveys and the online TSEP modules were completed in the	**Dependent Variable**: Nurse competence on IHI bundles, staging sepsis, HLCC, TeamSTEPPS **Measure**: The Nurse Competence Scale (NCS), comprised of a 73-item scale, was used to measure nurses' self-assessment of their competence across seven domains. Reliability testing of the NCS revealed Cronbach's alphas of 0.79 to 0.91. However, the possible pretest effects on internal and external validity were not discussed.	**Statistical Analysis and Tools**: Descriptive statistics, t-tests, and correlation analysis procedures were utilized. A Spearman correlation analysis was used to assess any association between modular posttest scores post-NCS scores. **Results**: A statistically significant improvement ($p < 0.0001$) was seen in knowledge posttest scores for the IHI bundles, staging sepsis. Statistically significant increases in ratings were found on the post-NCS survey for three sepsis-specific statements: 1. I feel competent to identify patients exhibiting the early signs and symptoms of sepsis. 2. I feel competent in my ability to care for patients diagnosed with systemic inflammatory response syndrome, sepsis, severe sepsis, and septic shock. 3. I feel competent to mobilize the health care team to begin early

			university’s computer banks.		goal-directed therapy to patients showing signs and sepsis symptoms (all $p < 0.0001$). **Conclusion**: The TSEP education program made nurses feel more competent on three sepsis-targeted statements which was shown by significant improvement in posttest knowledge after completion of the TSEP program.

Appendix B

Table 2

Synthesis Table

Evidence-Based Practice Question (PICO): Among adult patients with sepsis in a medical unit, does implementation of a Deterioration Index with Sepsis Narrator impact the unit's compliance with the 2016 Surviving Sepsis Campaign guideline?			
Level of Evidence	**# of Studies**	**Summary of Findings**	**Overall Quality**
I	**2**	In meta-analysis, Islam et al. (2019) found that the machine learning prediction models performed better than the existing sepsis scoring systems such as SIRS, MEWS, SOFA, and qSOFA for identifying and predicting sepsis patients three to hours before the onset. However, only seven studies were included. They evaluated different machine learning models for identifying sepsis rather than focusing on a few specific models. However, all the included models performed better than the traditional methods of sepsis in the identification and prediction of sepsis. In their SR, Damiani et al. (2015) found that after implementing performance improvement programs, there was an increased adherence to resuscitation and management sepsis bundles (6 hour and 24-hour bundles) and reduced mortality of patients from sepsis-related complications.	(B) Systematic review with meta-analysis with recent studies ranging from 2016 to 2018. Being an SR with the inclusion of many studies, no power analysis is required. Fairly definitive conclusions. Only three studies provided results of external validation. Model discrimination and calibration information was not included. The expertise of all involved authors is evident. (B) Consistent results with both sepsis bundles. An SR, therefore, no requirement for power analysis. Strength and limitations of all included studies provided. Recent studies from 2006 and 2014 were included. However, no RCT studies, only observational studies, were selected. Comprehensive literature review and the study provided an evaluation of the strengths and limitations of included studies. Expertise is evident.
III	**2**	Thursky et al. (2018) found significant improvement in patient outcomes and reduced costs after implementation of the hospital sepsis pathway (SP). This pathway has been successfully implemented in one other hospital in Victoria. Delaney et al. (2015) found that Taming Sepsis Educational Program® (TSEP™) made nurses feel more competent on three sepsis-targeted statements, shown by a significant improvement in posttest knowledge after completing the TSEP program.	B) No randomization of patients, but well-controlled study. No power analysis was reported, but in a study with 323 subjects—the first study to evaluate hospital-wide SP, an adequate reference was made with similar studies. Strengths and limitations of the study provided, with recommendations for further research. B) Sufficient sample size with power analysis with minimum to treat value provided. The difficulty of generalizing results from competencies with a self-assessment instrument. Pretest effect on posttest can pose a threat to internal validity—however, fairly definitive conclusions. The expertise of the authors is credible.

IV	**1**	Singh et al. (2021) found that the EDI effectively recognizes a small group of high-risk and low-risk patients with COVID-19, but it has low sensitivity as an early warning system for high-risk patients with COVID within 24 hours. However, patients with a low composite score within 48 hours had high sensitivity and negative predictive value.	C) No randomization of patients; convenience sampling with no power analysis was reported. Given the lack of power analysis, small differences between the two groups might not be detectable. Expertise credibility is established.

System for Hierarchy of Evidence

Level of Evidence	**Type of Evidence**
I (1)	Evidence from systematic review, meta-analysis of randomized controlled trials (RCTs), or practice guidelines based on systematic review of RCTs.
II (2)	Evidence obtained from well-designed RCT and/or reports of expert committees.
III (3)	Evidence obtained from well-designed controlled trials without randomization.
IV (4)	Evidence from well-designed case-control and cohort studies
V (5)	Evidence from systematic reviews of descriptive and qualitative study
VI (6)	Evidence from a single descriptive or qualitative study
VII (7)	Evidence from the opinion of authorities

Rating Scale for Quality of Evidence (Newhouse)

High (A)	Scientific	Consistent results with sufficient sample size, adequate control, and definitive conclusions; consistent recommendations based on extensive literature review that includes thoughtful reference to scientific evidence
	Summative Review	Well-defined, reproducible search strategies; consistent results with sufficient numbers of well-defined studies; criteria-based evaluation of overall scientific strength and quality of included studies; definitive conclusions
	Experiential	Expertise is clearly evident

Good (B)	Scientific	Reasonably consistent results, sufficient sample size, some control, with fairly definitive conclusions; reasonably consistent recommendations based on fairly comprehensive literature review that includes some reference to scientific evidence
	Summative Review	Reasonably thorough and appropriate search; reasonably consistent results with sufficient numbers of well-defined studies; evaluation of strengths and limitations of included studies; fairly definitive conclusions.
	Experiential	Expertise seems to be credible.
Low Quality (C)	Scientific	Little evidence with inconsistent results, insufficient sample size, conclusions cannot be drawn
	Summative Review	Undefined, poorly defined, or limited search strategies; insufficient evidence with inconsistent results; conclusions cannot be drawn
	Experiential	Expertise is not discernable or is dubious

Newhouse, R. (2006). Examining the source for evidence-based nursing practice. JONA. Volume 36, Number 7/8, pp 337-340

Appendix C

Figure 1

Monthly Blood Cultures Data

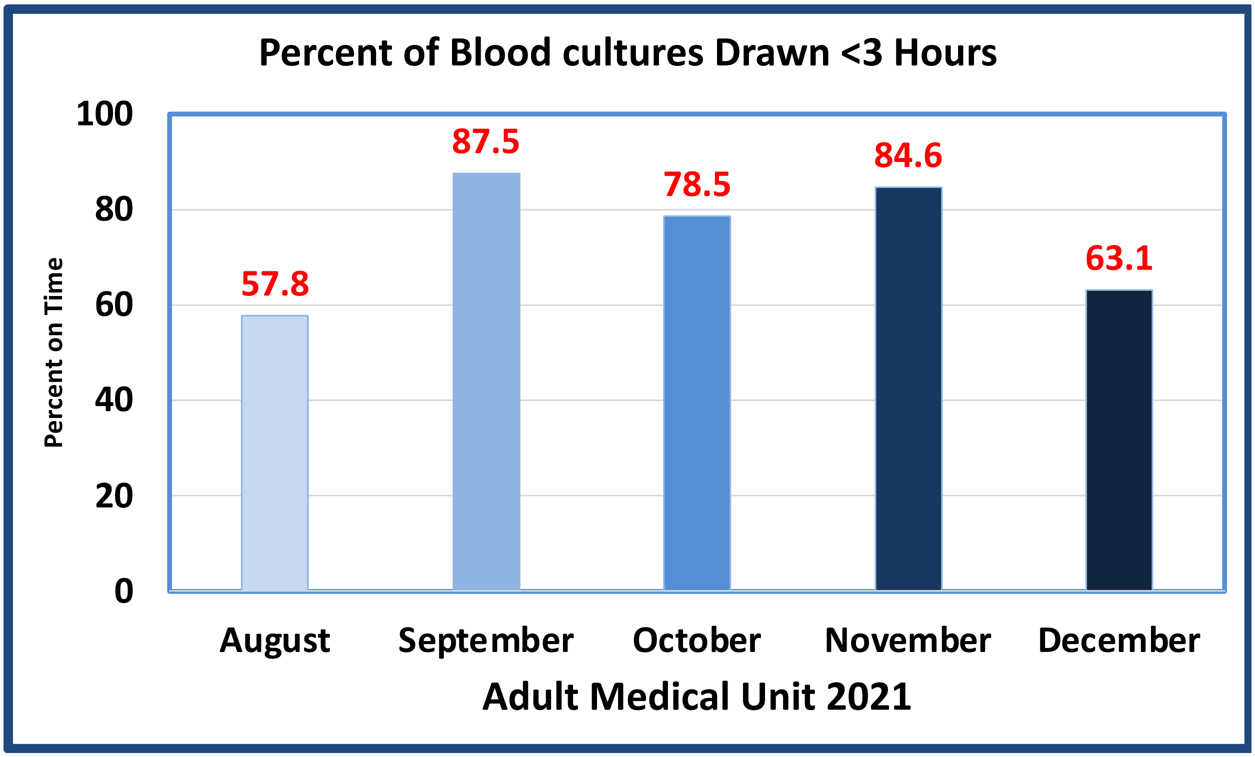


Figure 2

Monthly Length of Stay (LOS)Data

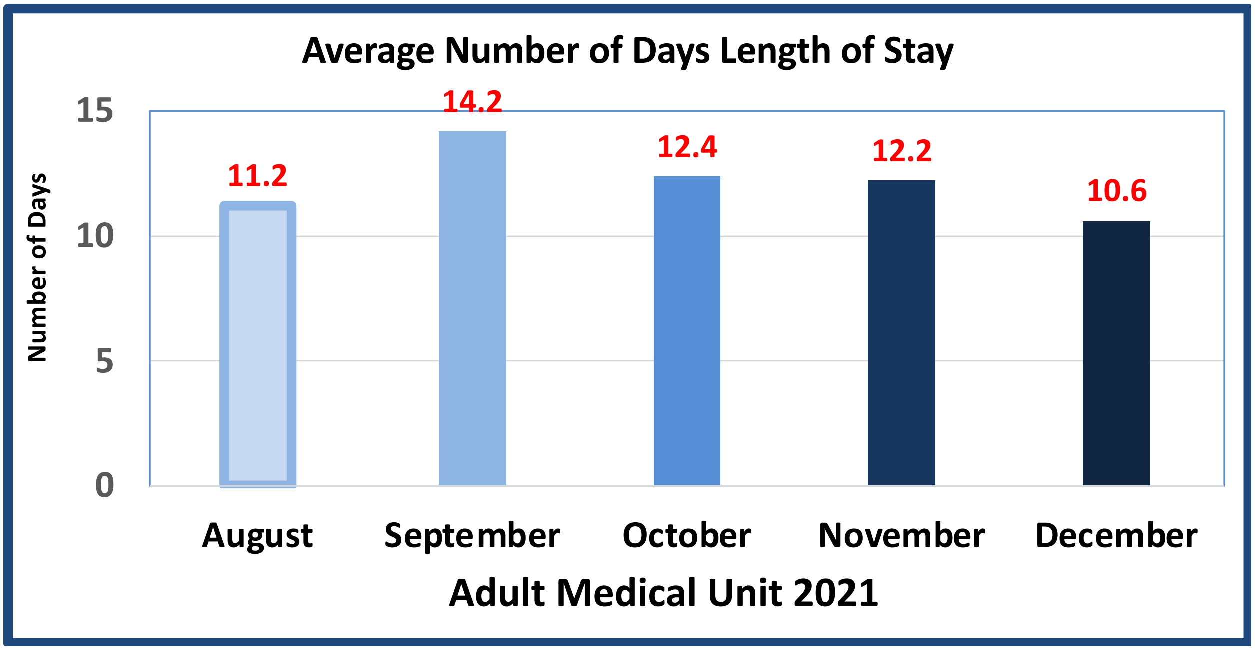


Figure 3

Weekly Blood Cultures Run Chart

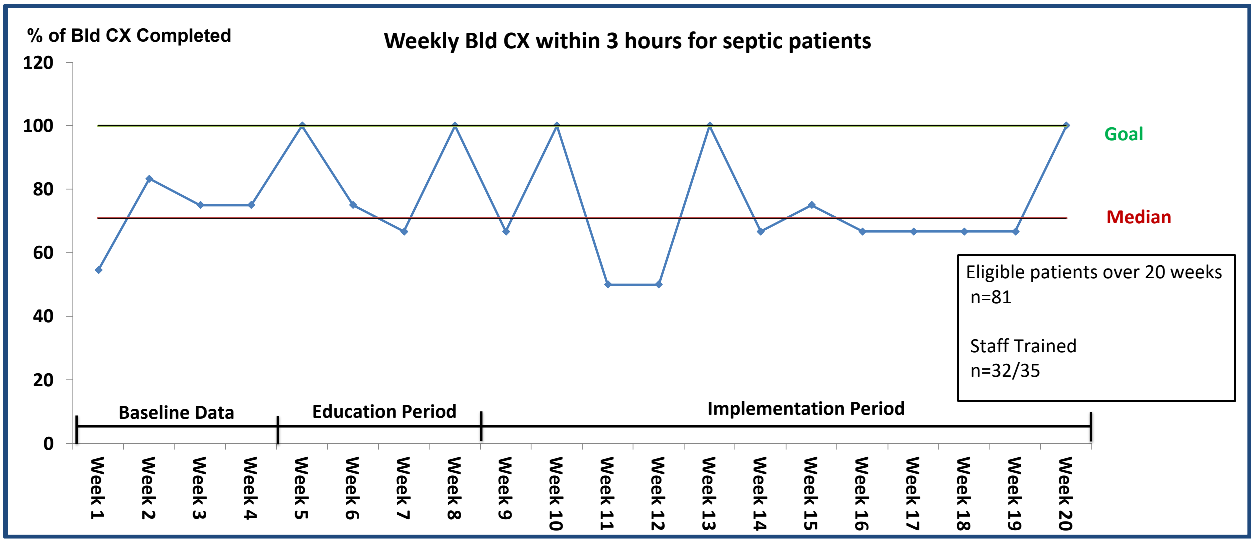
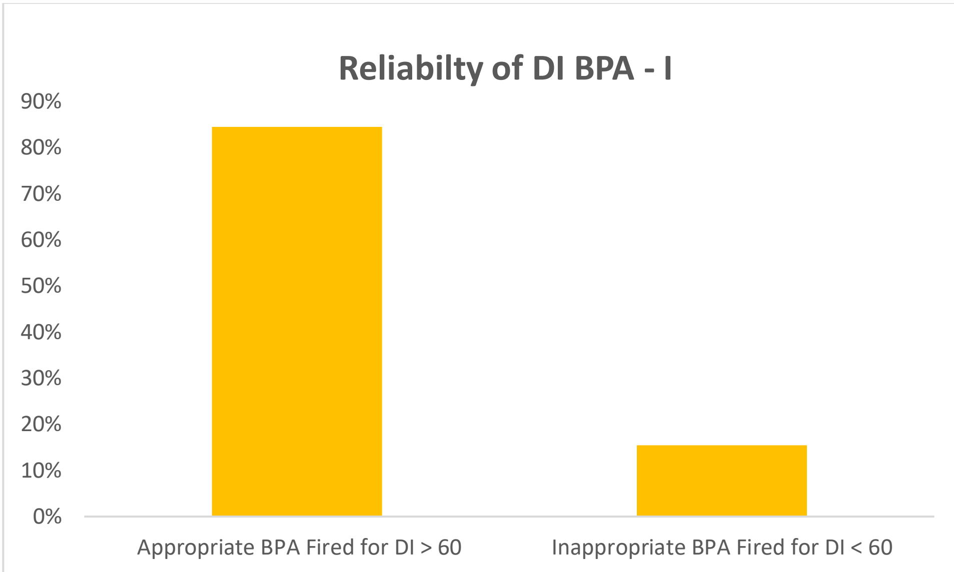


Figure 4

Reliability of DI BPA



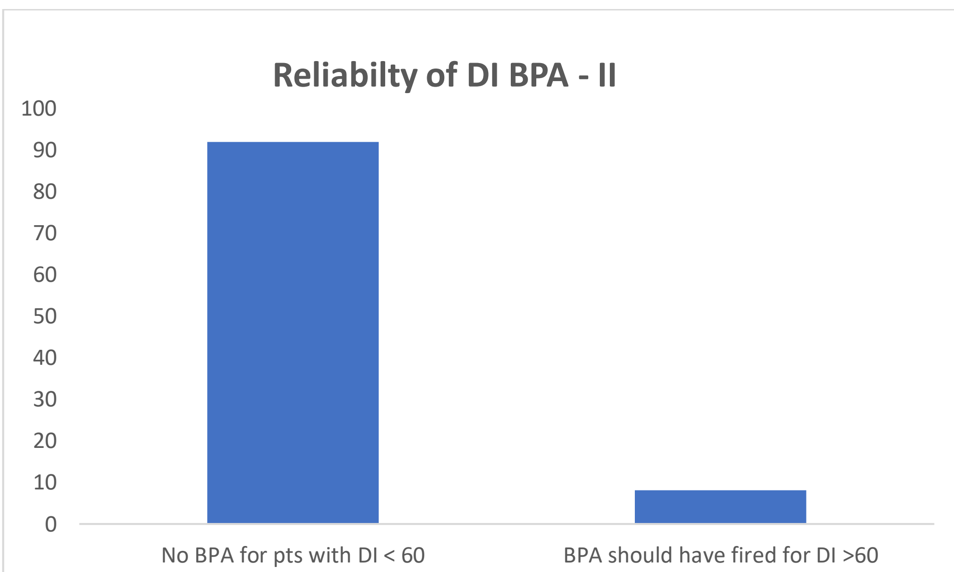
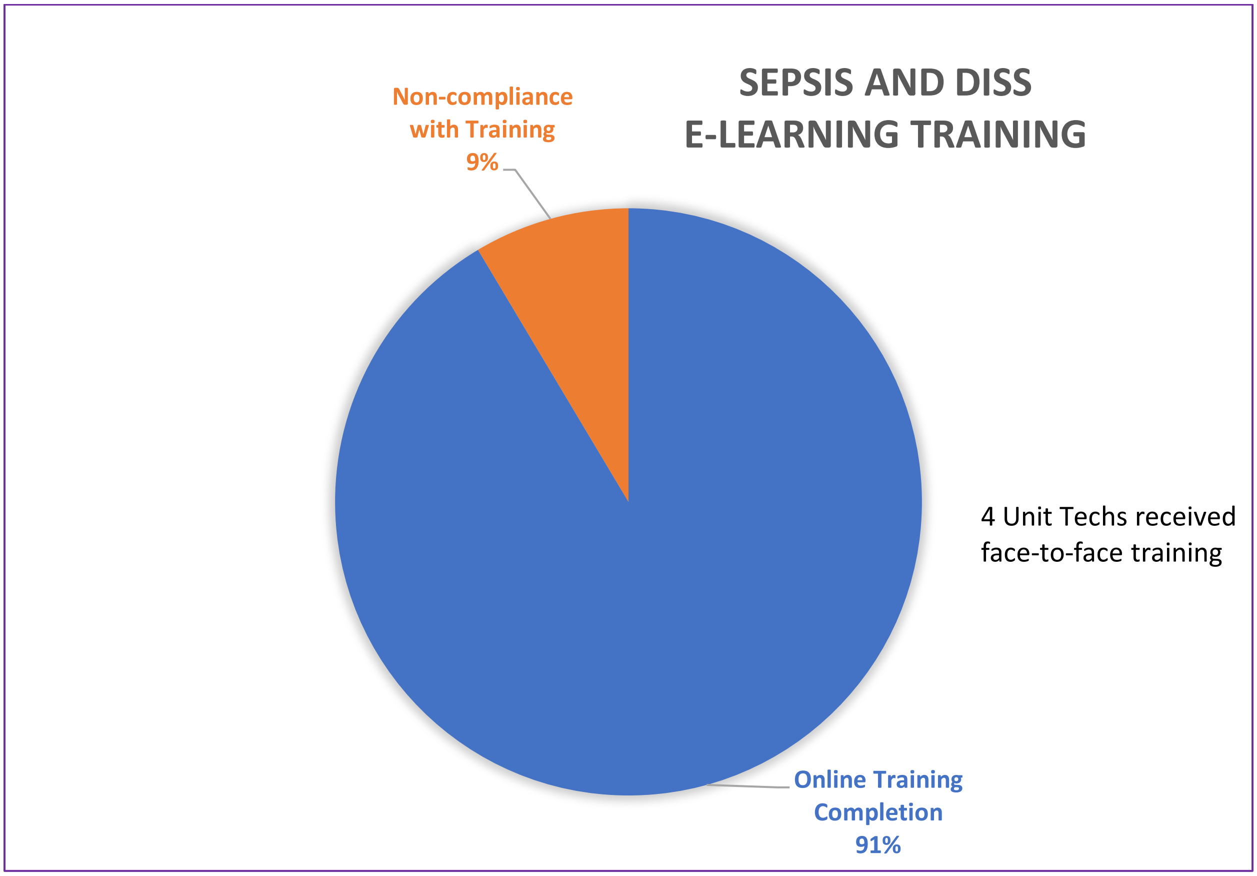


Figure 5

E-learning and Face-to-Face Training Attendance



Appendix D

Figure 6

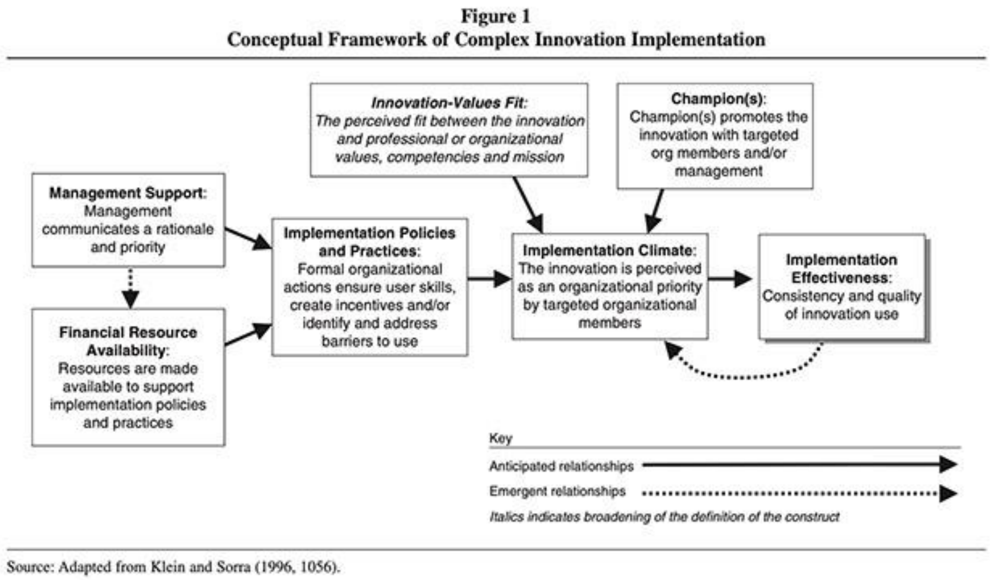
Kotter Eight Steps Process for Leading Change

Note. Source: https://www.kotterinc.com/8-steps-process-for-leading-change/

Appendix E

Figure 7

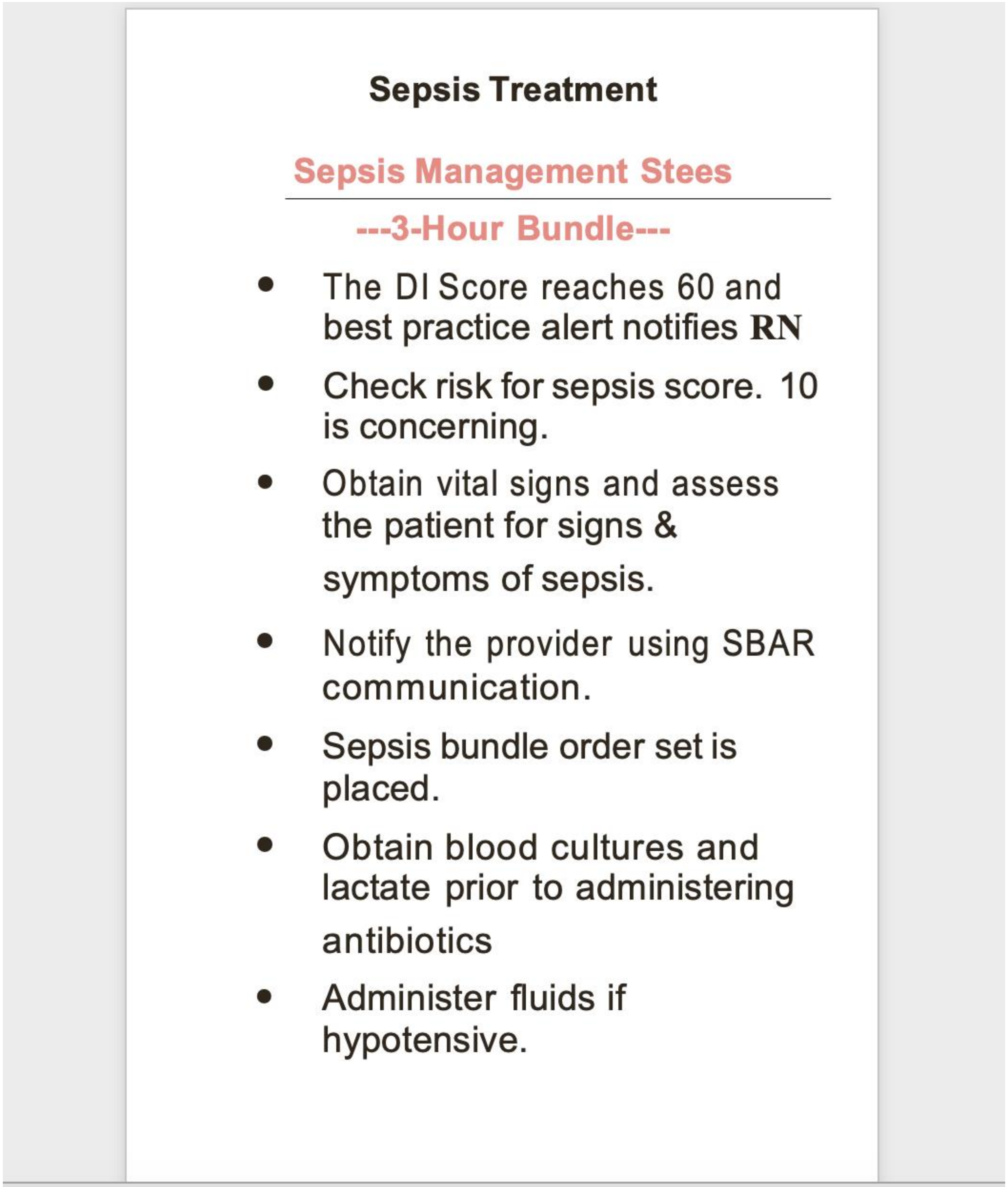
Conceptual Framework of Complex Innovation Implementation



Appendix F

Figure 8

Sepsis Bundle Badge for Nurses



Sepsis Treatment

Sepsis Management Stees

---3-Hour Bundle---

- The DI Score reaches 60 and best practice alert notifies **RN**
- Check risk for sepsis score. 10 is concerning.
- Obtain vital signs and assess the patient for signs & symptoms of sepsis.
- Notify the provider using SBAR communication.
- Sepsis bundle order set is placed.
- Obtain blood cultures and lactate prior to administering antibiotics
- Administer fluids if hypotensive.

Appendix G

Figure 9

Snapshot of Captivate E-learning Education on Sepsis and Deterioration Index