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Implementation of Artificial Intelligence Initiated Rapid Responses to Reduce In-Hospital Cardiac Arrest

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Abstract

Hospitals with strong and consistently activated rapid response teams (RRTs) have significantly fewer cardiac arrests. Early recognition of clinical deterioration supports the timely activation of RRTs, which increases earlier assessment and intervention. Current early warning tools are not sufficient and reliable for recognizing patient deterioration, and they are evolving, incorporating artificial intelligence (AI) to identify clinical decline much earlier. The project organization had previously implemented the medical early warning score tool into the RRT nurses' practice to prioritize patient assessments, but this was not sustained due to its unreliability in identifying patients at risk.

Aiming to reduce the number of in-hospital cardiac arrests by implementing AI to recognize and notify the RRT of patient deterioration, the primary key performance indicator was the number of in-hospital cardiac arrests outside the intensive care setting. Outcomes data also included the number of rapid responses pre- and post-implementation. Qualitative data were collected from the project team and RRT nurses during the implementation and self-assessment.

Outcomes showed decreased cardiac arrests from 13 to 9, but the pre- and post-intervention cardiac arrest rate remained the same at 7.2%. The number and rate of rapid responses increased as expected based on previous evidence from 1.04 to 1.25 per day, indicating that the addition of AI technology stimulated recognition of patient deterioration. With more time and data as we continue to improve AI implementation, we can better understand the true effect. Future utilization of AI technology to support faster, more reliable clinical warnings should be considered.

Keywords: *artificial intelligence, rapid response, cardiac arrest, quality improvement*

Section II: Introduction

Problem Description

Approximately 200,000 patients a year will have a cardiac arrest while hospitalized (Nallamothu et al., 2018), and of those, only 20% will survive to discharge (Churpek et al., 2012). Studies show that delays in recognizing deterioration can lead to cardiac arrest (Subbe, Duller, & Bellomo, 2017). Every minute of a delay in treatment of cardiac arrest can decrease the survival rate by 10% (Nallamothu et al., 2018). Despite standard treatment algorithms for advanced cardiovascular life support, variations in early interventions continue to correlate with low cardiac arrest survival rates (Nallamothu et al., 2018). Rapid response teams (RRTs) were created to address this gap, with early detection and interventions to prevent cardiac arrest and increase survival rates (Bingham et al., 2018). Hospitals with a rapid response activation rate of greater than 15 per 100,000 discharges had a significant decrease in the number of cardiac arrests (Astroth, Woith, Jenkins, & Hesson-McInnis, 2017). RRTs are effective if activated; however, RRT activation is dependent on clinical staff monitoring, identifying, and initiating the call to the team for help (Subbe et al., 2017). Automation of reliant early warning systems can increase rapid assessment and intervention, which could be achieved by using a real-time RRT calculation and notification system that is based on a statistically derived and validated score (Kang et al., 2016).

The organization for this evidence-based change of practice project setting is a non-profit, acute care hospital in California. The organization has 443 licensed beds with two campuses, which include 300 licensed beds at the Mountain View campus and 143 licensed beds at the Los Gatos campus. On average, the hospital has 202,662 outpatient encounters yearly and serves 400,000 annually (El Camino Hospital, 2019). The staff includes 1,300 registered nurses, 400 active physicians, 35 pharmacists, 110 laboratory staff, and 54 respiratory therapists.

In January 2006, in response to the Institute for Healthcare Improvement's 100,000 Lives Campaign (Simmonds, 2005), the organization implemented a rapid response alert procedure. The new procedure allowed any hospital staff to call a rapid response alert if a patient met any of the defined clinical criteria. Shortly after the RRT formed, the RRT nurses began proactively reviewing active patient records to identify deteriorating patients. The chart review process was time consuming, and it did not have a set methodology, so practice varied. In November 2015, with the implementation of a new electronic health record (EHR), the decision was made to use the medical early warning score (MEWS) tool to prioritize which patients the RRT nurses would proactively evaluate for deterioration. However, because MEWS did not reliably and accurately identify patients at risk for deterioration, the tool was not incorporated into the RRT nurses' daily practice.

The organization's response to clinical deterioration was shifting. Between January 1, 2018, and December 31, 2018 (calendar year 2018) there were 63 code blues for cardiac arrest and 648 rapid response alerts. Between January 1, 2019, and December 31, 2019 (calendar year 2019) there was an increase of code blues for cardiac arrests to 80 and a decrease of rapid response alerts to 356. The organization's performance was compared with the external risk-adjusted benchmark information from Premier Quality Advisor Top Quartile, and while the hospital's risk-adjusted mortality index was 1.0 and on target, the organization had an internal goal for an improved quality outcome of a 0.95 mortality index score.

Available Knowledge

PICOT Question

The patient/problem, intervention, comparison, outcome, time (PICOT) question for this project is: In adult inpatients (P), how does implementation of an artificial intelligence based automated early warning system (I), compared to nurse-driven activation of rapid response (C), effect in-hospital cardiac arrests outside the ICU setting (O) over a six-month period (T)?

Search Methodology

A search of the literature was limited to adult inpatient studies in English between 2014 and 2020. Cochrane, CINAHL, PubMed, Medline, and Scopus databases were used to find articles related to the PICOT question and resulted in 4,758 studies (280 Cochrane, 2,966 CINAHL, 53 PubMed, 1,458 Medline, and one Scopus). Narrowing the search words to only *auto* and rapid response and cardiac arrest, safety,* and *quality* resulted in 71 peer-reviewed studies. Studies considered for review met the following inclusion criteria: focused on adult patients (> 18 years old) in the acute-care hospital setting; described the impact of rapid response teams on quality outcomes; compared clinical deterioration recognition tools; offered interventions shown to enhance rapid response systems; were published between January 2014 and September 2020; and were published in English. The exclusion criteria were articles that did not contain original research; included pediatric patients; limited to specialty area (e.g., emergency department); conducted outside of the acute-care hospital setting; focused on the rapid response team makeup; analyzed the cost of rapid response teams; had a limited sample size, or that focused on hardware. After eliminating articles not relevant to the study aim or duplicative, 30 studies remained for manual review.

Search Outcome

The Johns Hopkins research evidence appraisal tools (Dang & Dearholt, 2018) were used to determine the level and quality of each of the articles reviewed. An evidence evaluation table was then created using Johns Hopkins individual evidence summary tool (Dang & Dearholt, 2018) to summarize the articles (see Appendix A). Twenty two studies were excluded: five were expert opinion, three focused on the RRT development, three had limited sample size, one had weak results, one focused on hardware, and nine others had findings covered in higher quality articles. The 11 reviewed articles are the most relevant and robust for the area of interest. The evidence levels were limited to the most rigorous studies of good to high quality, which resulted in three Level I systematic reviews (Gao et al., 2007; Lyons, Edelson, & Churpek, 2018; Winters et al., 2013); four Level III quantitative studies (Angel, 2016; Churpek et al., 2012; Churpek, Yuen, Park, Gibbons, & Edelson, 2014; Subbe et al., 2017); two Level III qualitative studies (Astroth, Woith, Stapleton, Degitz, & Jenkins, 2013; Wakeam, Hyder, Ashley, & Weissman, 2014); one Level III mixed methods study (Astroth et al., 2017); and one Level V article, a summary of expert opinion from a national conference (Rojas, Shappell, & Hube, 2017).

Review of the Evidence

A review of the literature helped to define the problem further and to identify quality and safety initiatives to improve patient outcomes. Angel (2016) described the evidence on the value of a high-quality RRT. Although this study had a limited sample size, the researchers of this retrospective correlational study, suggested that early intervention from a knowledgeable and experienced RRT could reduce the occurrence of cardiac arrest and improve patient outcomes.

Focusing on the strengths and weaknesses of rapid response systems (RRSs), Astroth et al. (2013) conducted a qualitative study and found that team characteristics and unit culture were barriers to staff calling rapid responses. The researchers identified level of nursing experience and level of education as barriers to RRT activation (Astroth et al., 2013). The strengths of the RRT were further examined by Astroth et al. in 2017, in a study in which they developed and tested a tool to identify the specific factors and barriers to RRT activation. They concluded that RRTs that included not only team members that were knowledgeable, but supportive in sharing their knowledge with the staff that called the rapid response, were more successful in promoting the use of the RRS and contributed positively to the organizational culture.

Within a quality assurance framework, Lyons et al. (2018) reviewed the current aspects of RRSs, identifying that while rapid responses may decrease inpatient mortality and the number of cardiac arrests, future work on understanding the human factors that influence RRSs, as well as possible advancements in monitoring and informatics technologies that could enhance these systems, is needed.

Incorporating automation from early warning systems into an RRS was tried and evaluated by Subbe et al. (2017). This study found that quality was improved with automation, as there was an increase in the number of RRT alerts. With a decrease in the rate of cardiac arrest from 3.5% in the control period to 0.4% in the intervention period, the researchers concluded that the automated warning system had a significant influence in preventing cardiac arrest.

In their study describing the quality of the available track and trigger warning systems, Gao et al. (2007) reviewed the reliability, validity, and utility of these tools. They found the sensitivity and positive predictive values were low, retrospectively, with median (quartiles) of 43.3 (25.4-69.2) and 36.7 (29.3-43.8). This systematic review concluded that there is low sensitivity of hospital-developed warning systems, which leaves patients vulnerable to not having their clinical deterioration recognized and should, therefore, be used only to aide with clinical assessments. After completing a meta-analysis, Winters et al. (2013) concluded that the implementation of an RRS was associated with a statistical reduction in non-ICU cardiorespiratory arrest (RR, 0.66 [95% CI, 0.54 to 0.80]). Focusing on the need for quality improvement of RRTs, they summarized that outside of the intensive care unit (ICU), signs of patient deterioration are frequently unrecognized, track and trigger tools are not reliant, and RRTs are underutilized.

Addressing the patient safety issue of delay in clinical intervention, Wakeam et al. (2014) identified failure to rescue barriers, such as poor communication, insufficient training, and lack of ownership. They then identified strategies for improvement, which included having RRTs, utilizing data from the EHR to recognize signs of deterioration earlier, structured communication tools, and standardized care pathways.

More recently, Rojas et al. (2017) summarized annual conference presentations from the International Conference on Rapid Response Systems and Medical Emergency Teams to form a synopsis of the current thoughts in the field. Overall, the investigators found there is a strong adoption of RRSs. However, they concluded, there is a need for integration of subjective and objective data from the EHRs to develop safer, more reliable, and accurate RRS notifications.

Churpek et al. (2012) published their work on developing a more accurate cardiac arrest prediction tool. The researchers found that the multivariable logistic regression tool they developed more accurately predicted cardiac arrest a median of 48 hours sooner than the commonly used MEWS. Later, the tool was expanded to incorporate vital sign, demographic, and laboratory data already available in the EHR (Churpek et al., 2014). Churpek et al. (2016) further expanded this work in a study comparing the accuracy of machine learning methods to MEWS for detecting clinical deterioration. Overall, the researchers found clinical deterioration was more accurately predicted by machine learning methods (AUC 0.77 vs. 0.74; $p < 0.01$) than the MEWS (AUC 0.70 [95% CI 0.70–0.70]). These findings support the PICOT intervention of implementing an artificial intelligence (AI) based automated early warning system to support RRT activation.

Rationale

Description of the Conceptual Framework

A combination of Lippitt's classic theory on the dynamics of planned change (Lippitt, Watson, & Westley, 1958) and the integrated Promoting Action on Research Implementation in Health Services (i-PARIHS) framework (Kitson & Harvey, 2016) along with the nursing process forms the conceptual framework that guided the search for evidence and the development of this evidence-based, change of practice, quality improvement project (see Appendix B). In 1958, Lippitt et al. were the first to describe Lippitt's phases of change theory as an evolution of Lewin's three-step change theory. Aligning with the nursing process of assessment, planning, implementation, and evaluation, Lippitt's theory of change is broken down into seven phases (Mitchell, 2013). Developed in 2016, the i-PARIHS framework by Alison L. Kitson and Gillian Harvey describes that a successful implementation includes the quality of the evidence, the context of the evidence, and the level of facilitation needed to implement familiarity translation into practice (Kitson et al., 2008). The i-PARIHS framework further adds direction for the various levels of necessary facilitation and the facilitator's role in implementing knowledge translation (Kitson & Harvey, 2016). This framework guided the review of the evidence establishing how the work is to be sequenced. Lippitt's change theory defines each of the project phases, and i-PARHIS describes the change agent activities.

The review of the evidence began with the assessment phase, which identified three studies (Angel, 2016; Gao et al., 2007; Subbe et al., 2017) that added to defining the problem. These studies also related to Phase 1, diagnose the problem of Lippitt's change theory and the i-PARHIS framework characteristics of the innovation, in which the facilitator identifies the problem. Next, the evidence reviewed focused on a study that analyzed the characteristics of high-quality RRSs (Winters et al., 2013), aligning with Lippitt's Phase 2, assess the motivation/capacity for change, and i-PARHIS recipients focus area. In Lippitt's Phase 4, select a progressive change object, and i-PARHIS inner context local level, the intervention is described as the evolution of a reliable machine learning automated RRS (Churpek et al., 2012; Churpek et al., 2016). Finally, with sustainment in mind, the research focused on the characteristics of top-performing hospitals (Rojas et al., 2017), how to address common barriers for effective RRTs (Astroth et al., 2017; Astroth et al., 2013), and how RRTs incorporate technology to support human characteristics. This evidence can be used to guide project implementation, which relates to Lippitt's Phase 6, maintain change, and the i-PARHIS outer context focus area (Kitson & Harvey, 2016; Mitchell, 2013).

Specific Aims

The project aim was to develop, implement and evaluate a RRT activation program to reduce in-hospital cardiac arrest outside the ICU setting by increasing the reliability of RRT activation through the implementation of an AI driven notification system by July 2020. Epic's machine learning deterioration index AI module was implemented into the target organization's EHR. Using the plan-do-study-act (PDSA) quality improvement process, automated alerting was integrated into the established RRS to increase earlier recognition, notification, and patient deterioration intervention and, therefore, reduce in-hospital cardiac arrests outside the ICU setting.

Section III: Methods

Context

The key stakeholders included the project team members, the organization's CPR committee, direct care nursing staff, respiratory therapy staff, and medical staff. The team, led by the DNP student, the nursing director of cardiovascular services, included representatives from clinical informatics, patient care services, the RRT, and clinical education. The steering committee, also led by the DNP student, included the chief nursing officer (CNO), chief medical officer (CMO), chief information officer (CIO), nursing director for patient care services, nursing director for Los Gatos campus, and nursing director of clinical education.

During the planning phase, executive support of the CNO, CMO, and CIO was acquired, and a letter of support from the CNO was obtained (see Appendix C). The project charter was then approved by both the CNO and CIO (see Appendix D). An overview of the project idea was then communicated to the organization's clinical leaders, the CPR committee, and the RRT for buy-in and support.

Intervention

The project's scope was to implement Epic's deterioration index AI module and incorporate automated alerting functionality into the organization's current rapid response process. The main objective was to form a team to determine the automated notification criteria, using the AI technology to augment RRT activation and develop new workflows to incorporate the AI into the RRT nurses' routine assessments of patients at high risk for deterioration. The team defined the deterioration risk levels, established the appropriate automated notification criteria, determined the display formatting of deterioration index information in the EHR, and developed the new workflows.

The deterioration index AI model is an ordinal logistic regression program that arranges patients into risk categories based on the likelihood that patients will be transferred to the ICU, have a rapid response alert, cardiac arrest, or die during their hospital stay. Epic used information from 2012 to 2016 from approximately 325,000 observations over 130,000 patient encounters to develop the deterioration index AI model (Epic, 2020). This tool examines demographic information, vital signs, lab results, and nursing assessments for each patient each time a new result or observation is documented in the EHR, resulting in approximately 125 points of analysis.

The AI analysis produced a deterioration index score for each adult inpatient. This score was used as the primary criterion for automated notifications. Initially, the team planned to alert the entire RRT with automated notifications. However, during the implementation, the team determined that only the RRT nurse and the nursing unit charge nurses would receive automated notifications via the organization's wearable communication device, in the form of a text message and an audio tone, later as a full text to speech announcement.

During the PDSA implementation iterations, the logic rules for the automated notifications evolved based on the RRT nurses' feedback on the sensitivity to reduce the risk of alert fatigue. Based on The Joint Commission (TJC) recommendations related to alarm systems (TJC, 2013), the team identified situations when notifications were not clinically necessary and tailored notification settings for individual patient groups to minimize alerts. The automated notifications' final criteria were adult inpatients with a deterioration index value of 62 or more or a 15 or more point increase of the patient's deterioration index score within 35 minutes. Patients in procedural areas and patients with comfort care orders or admitted as general inpatient hospice were excluded. To continue minimizing alerts, once indicated in the EHR that the patient's condition was reviewed, notifications would be suppressed for that patient for 8 hours and 24 hours for patients with *do not resuscitate* (DNR) code status orders.

The team also developed new standard workflows for the RRT nurses (see Appendix E). A change of shift workflow detailed the RRT nurse's process for reviewing patients with clinical deterioration from the previous shift and any patients in the included departments meeting the defined high-risk threshold for deterioration. Next, workflows were designed on how the RRT nurses would track significant changes in the patient's deterioration index score, any AI-initiated RRTs, and any staff-initiated RRTs. The expected outcomes were to increase the number of rapid responses and decrease the number of in-hospital cardiac arrests outside the ICU setting.

Gap Analysis

A gap analysis was conducted comparing the organization's current state and the future state with the proposed project intervention in place (see Appendix F). The current state was that the organization had an established RRT that was being activated if a patient met any defined clinical criteria or if the staff had concerns about the patient's clinical presentation. The gaps identified were that although the RRT nurses were taught to use the MEWS tool to assess patients for deterioration proactively and to use the tool to prioritize which patients they would conduct an in-person assessment, because MEWS did not reliably and accurately identify patients at risk for decline, it was not adopted into practice. There was also a possible failure to recognize patient deterioration and delays in RRT activation, as reflected by an increase in code blue cardiac arrest and decreased RRT activations from 2018 to 2019. This information supported the future state that addressed the need to recognize patient deterioration and the augmentation of RRT activation. The literature also supported the earlier activation of RRTs through an automated alert system based on AI technology to decrease the rate of in-hospital cardiac arrests. Overall, the previous literature and the organization's current state and gaps supported this project to implement Epic's deterioration index AI module into the organization's RRS to increase earlier identification, notification, and intervention to improve clinical outcomes and reduce cardiac arrest.

Gantt Chart

A Gantt chart provided a detailed list of the needed tasks and included the anticipated start and end dates throughout the project phases. The Gantt chart served as a tool to track progress throughout the phases, and when needed, adjustments were made to the schedule. Based on the conceptual framework, the Gantt chart was broken down into five sections: assessment, planning, implementation, evaluation, and project termination. Each section included critical milestones for the project (see Appendix G).

The two critical milestones in the assessment phase were determining the feasibility and obtaining support. The assessment phase was February to April of 2019. The first milestone was to establish that the intervention was even feasible and that its EHR system could support AI. Once that was confirmed, the DNP student was able to move to the milestone of securing executive sponsorship. A Project Charter was presented to the CIO, CNO, and CMO to secure the project's support.

In the second phase, planning began in May 2019 and lasted through January 2020. The key milestones included establishing the workgroup, defining project scope, describing the detailed intervention specifications, and designing communication and training plans. This phase took longer than anticipated because the AI software needed 90 days to mature in the organization's EHR. This time then had to be extended 30 days due to a configuration issue.

The implementation phase was dependent on the completion of the planning phase. Implementation started in February 2020, but because of the COVID-19 pandemic, the project was put on hold for eight weeks. The PDSA cycles resumed in April 2020 and were completed in July 2020. The milestones in this phase were hospital-wide communication and training of the modifications to the RRS, followed by activation of the AI notification into the RRS.

The last two phases mapped out using the Gantt chart were the evaluation and project termination phases. While evaluation was ongoing throughout implementation via the PDSA process, the outcome metrics were evaluated in August 2020. The key milestones in these phases were post-activation data collection, analysis, and monitoring. During the PDSA cycle implementation, it was anticipated that there would be needed adjustments to the notification criteria and the RRT nurse workflows. Discussions of the needed adjustments occurred in the ongoing project meetings. Once the specifications and workflow were solidified and sustained, the DNP student initiated the project termination phase.

Work Breakdown Structure

This project's work breakdown structure was divided into the five phases of the nursing process (see Appendix H). Starting with the assessment phase, tasks included a review of the evidence to support the rationale for implementation, analysis of the current rapid response performance data, readiness for change assessment, and a system feasibility check with the information technology (IT) team. This information was useful in the development of the project charter.

As the project moved into the planning phase, the focus was on finalizing the team members, establishing regular team meetings, and reviewing the project scope. During the kick-off meeting, the team defined the key performance indicators (KPIs) used to compare baseline performance with post-activation performance. Based on the evidence, the KPIs chosen included the number of code blue cardiac arrests outside the ICU setting and the number of rapid responses.

Once the outcome measures were determined and the steering committee approved the final project plan, communication to all the clinical leadership began. Then, work started in developing the new workflows and working with the IT team to determine the organizational specific configuration of the deterioration index. This phase included the time needed to allow the AI software to mature within its EHR. Once the AI was mature, the team reviewed the software vendor’s analysis of the organization’s AI performance and conducted a retrospective analysis of the AI’s identification of patient deterioration to previous cardiac arrest and rapid response events to determine the initial notification threshold criteria. In the planning phase, the team also designed how the AI scoring data would be displayed in the EHR to the clinical staff. Lastly, the training and communication plan was developed.

The implementation phase included making the needed EHR changes available in the live system and starting the automated notification, via the wearable device, based on the defined trigger criteria. Through the PDSA process, the AI-driven notification criteria and workflows were implemented and adjusted. After numerous PDSA cycles, the final criteria and workflows were in place. During the last few phases of the PDSA implementation process, integrating the AI into the RRS was communicated to the direct care staff. Once the final automated notification criteria and workflows were stable, a communication was shared with the medical staff on the enhancement to the organization’s RRS.

The evaluation phase began when the AI-driven notifications and new workflows were incorporated into the RRS and lasted through July 2020. For sustainment post-activation, the team continues to meet to review any issues related to adoption and monitors clinical outcomes.

Finally, the project moved into the termination phase in August 2020. All project files and records were updated in this phase, any materials archived as needed, and formal acceptance gained. The DNP student collaborated with the team and steering committee to document lessons learned and celebrate the accomplishment of a well-executed project and improvement in clinical outcomes.

SWOT Analysis

During the project's assessment phase, a strengths, weaknesses, opportunities, and threats (SWOT) analysis was conducted to help determine the overall feasibility and needed areas of focus to support the project's success (see Appendix I). The strengths internal to the organization were identified as having Epic in place, access to Epic resources, an established RRT, and alignment with organizational goals. The three key organizational goals that were supported by this project were the organization's core value of innovation to embrace solutions and forward-thinking approaches that lead to better health (El Camino Hospital, 2020), the strategic goal to reduce mortality, and the Heart and Vascular Institute's goal to prevent cardiac arrest. External opportunities included RRT nurses' inconsistent use of the embedded MEWS tool, lack of reliability and accuracy of the MEWS tool, and RRT activation dependent on a nurse action. Internal areas of weakness identified were competing priorities and projects, resource allocation and stakeholder buy-in, and staff's mistrust of the *black box* AI calculations. Lastly, external threats to the project's success to be addressed included medical staff engagement and acceptance and reliance on other organizations to share implementation methodologies. Initially, there was a concern that other organizations would be unwilling to share their experiences with implementing and utilizing the deterioration index. However, after attending the annual Epic user group meeting, several organizations presented, so this was not a threat to the project.

Budget

The project budget included the labor cost for staff to participate (see Appendix J). The estimated cost of labor to participate in the project and ongoing stabilization meetings was $66,641 for the first 18 months. Approximately $19,460 (29%) of the estimated budget was for the nurse leader's time. In 2015, the organization implemented Epic's EHR for around $150 million (Miliard, 2015). This software's ongoing cost was included in the overall organization's 2020 IT capital budget of $6 million (Woods, Hussain, & Griffith, 2019), there was no delineated line item in the budget for this Epic software. Therefore, software costs were not included in the project budget.

Cost/Benefit Analysis

The three options for reducing cardiac arrest outside the ICU in the organization were analyzed for their financial impact (see Appendix K). To make no change to the organization's RRS, the first option would have no projected cost-benefit, essentially a return on investment (ROI) of 0. This option would cost the organization approximately $3,357 for the project lead and other stakeholders' time in analyzing the options based on the hourly personnel rate.

The second option, to implement an AI-driven recognition tool to detect patient deterioration and trigger the RRT automated activation, would yield the highest ROI of 5.85. Other organizations that have implemented this solution have reported significant reductions in codes outside the ICU. Ochsner Health reported a 44% reduction, and North Oaks reported a 39.3% reduction (Ho, 2018; Robinson & Tyler, 2019). Based on these reported outcomes, it was estimated that this solution could reduce the number of inpatient cardiac arrests outside the ICU by approximately 42%. In the calendar year 2019, there were 80 codes in the organization. with 38 outside the ICU. A 42% reduction would be an estimated 16 fewer codes per year. Calculating in the code team hourly rate, code medication, and supply costs, each code would cost approximately $2,061. Factoring in inflation, a reduction of 16 codes per year could yield the organization a cost avoidance of $8,621 over the next four years. An additional cost savings was determined using a statistically developed average value for a year of quality human life of $129,000 (Lee, Chertow, & Zenios, 2009). Assuming at least one human life would be saved through this solution each year and calculating inflation, there is a potential for an additional $539,688 cost avoidance. The total cost savings with this option was estimated to be $677,627 over four years. The expenditures would be the cost of the project lead and other stakeholders' time during the project. The team would need more time to meet through the project's assessment, planning, and implementation phases. Afterward, the team would continue to meet during the evaluation and project termination phases, but with reduced frequency to monitor and support sustainment. Based on the hourly personnel rate, factoring in a 10% contingency and a 3% inflation rate, this option would be approximately $98,862 for the organization over four years.

The third option was to continue with the current early warning system but add automation of RRT activation. This option would offer a moderate ROI of 4.92. Cost avoidance calculations regarding code events were based on the assumption that this option would prevent at least one code a year. Estimating the cost of the code team's hourly rate, code medication, and supply costs, each code costs approximately $2,061. Factoring in inflation, reducing one code per year could save the organization $5,839 over the next four years. An additional cost savings was determined using a statistically developed average value for a year of quality human life of $129,000 (Lee et al., 2009). Assuming at least one human life would be saved through this solution each year and calculating inflation, there is a potential for an additional $539,688 cost avoidance. The total cost savings with this option could be $548,309 over four years. Similar to option two, this option's expenditures would include the cost of the project lead and other stakeholders' time. The team would need more time during the assessment, planning, and implementation phases of the project than the evaluation and termination phases. However, because this solution does not include implementing the AI recognition tool, the team would not need time in the assessment and planning phases. Based on an hourly personnel rate, factoring in a 10% contingency and a 3% inflation rate, this option would be an approximate $92,574 expenditure for the organization over four years. Although this option has a similar ROI as option two, this option will likely over-identify patients as at-risk, thereby over alerting the RRT nurses, which would result in alert fatigue. The term alert fatigue describes how clinicians become desensitized to safety alerts and, consequently, fail to respond appropriately (Henneman & Rothschild, 2019). Alert fatigue is a serious risk that could result in the RRT nurse not responding to a notification of the patient's condition change; thereby, the patients would not benefit from early intervention.

Overall, based on the analysis of these three options, the organization's executive team approved the second option. The first option to remain the status quo would be the least valuable, and the third option had a high risk of failure due to alert fatigue. The second option, to implement Epic's deterioration index AI module and build in the automation of RRT activations best addressed the organization's need for more reliable recognition and earlier activation of their RRT. The evidence had also shown that this solution would reduce the number of cardiac arrests, which would improve patient outcomes.

Return on Investment Plan

The ROI for this project was calculated on avoiding costs associated with cardiopulmonary resuscitation and litigation related to loss of life. Based on other organizations' performance, an estimated reduction of 16 cardiac arrests outside the ICU per year, plus the average value for a year of quality human life, came to a total cost avoidance of $161,971. The total costs for implementation were based on the labor costs for stakeholders' time for startup and first year of implementation, which was estimated at $66,640. The estimated cost avoidance and labor costs would yield an estimated year one total net savings of $95,331 and an ROI of 1.43. Over the next three years, the ongoing cost to sustain and maintain the intervention is estimated to be $32,221 ($10,740 per year). The ongoing cost is significantly less than startup and first year of implementation, resulting in an increased ROI of 15 for 2021, 2022, and 2023 and an overall ROI of 5.85(see Appendix L).

Responsibility/Communication Plan

A responsibility and communication matrix was developed to ensure that all stakeholders and impacted staff received information on changes to the rapid response process (see Appendix M). This matrix identified stakeholders who would require communication throughout the project and included the principal executives, the project team, clinical and medical staff leadership, clinical education, the CPR committee, and the direct care nursing and medical staff. For each stakeholder group, the matrix described the objectives, format, timing of when and how often the communication would occur, and the responsible person. The DNP student owned the majority of the responsibility for communication. Such communications included monthly in-person meetings with the CNO to give an update on project status and to communicate any barriers to project success that needed executive-level assistance.

Quarterly, during regularly scheduled meetings with clinical leadership, information on project status and any needed support requests were presented. At the monthly CPR committee meeting, brief status updates were also presented. The team met every two weeks; meetings reviewed progress, follow-up tasks, and responsibilities. The DNP student worked with the Clinical Education Department to teach the RRT nurses the new standard workflows for incorporating the AI into their regular practice (see Appendix N) and to develop and distribute education for all hospital staff on the AI enhancement to the RRS (see Appendix O). Through presentations at the Quality Council, Department of Medicine meetings, and in a newsletter to all medical staff, the DNP student also worked with the medical staff office to inform the physicians practicing at the organization of the addition of AI to augment RRT activation.

Project momentum was maintained with in-person meetings, using slide presentations to illustrate the information. Combining in-person presentations with colorful slides helped engage the audience on the need and importance of the project. Due to busy schedules, executives received in-person briefings on project status, and formalized meetings were limited to address issues that required executive-level assistance. Initially, the team met in person with a call-in number for members at the other campus. However, since the emergence of the COVID-19 social distancing rules, project meetings moved to a web-conferencing platform. Meeting agendas and minutes were used with the team to maintain engagement by communicating decisions, action items, and timelines.

Shortly before implementing changes to the RRS, the Clinical Education Department led a campaign of informational fliers and department huddles to communicate to direct care staff.

Timing and saturation of this effort were crucial because if provided too early, staff could forget about the upcoming changes; if too close to the process change, some team members may have not yet received the information and may become upset for not understanding expectations.

Study of the Intervention

To assess the impact of the project aim, quantitative and qualitative approaches were used. The quantitative data included the number of cardiac arrests outside the ICU setting, the number for rapid responses, and the number for AI notifications. As the highest level of care in the organization, the ICU settings were excluded from the intervention and excluded from the outcome measure. Other areas excluded from the intervention and outcome measure were the emergency departments and procedural areas, such as Interventional Services and Endoscopy.

The qualitative data comprised team feedback collected during project meetings and from the rapid response nurse standard work self-assessment survey. During project meetings, RRT nurses gave feedback on the automated notification criteria, standard workflow processes, and the implementation processes. In early project meetings, the variation in RRT nurse practice was identified. Once the standard workflow process for incorporating the AI into the RRS was defined and implemented, the RRT nurses participated in a self-assessment survey, collecting information on their adoption and adherence to the new processes at the end of each shift.

Measures

This project's primary key performance indicator was the number of in-hospital cardiac arrests outside the ICU setting pre- and post-implementation. The CPR committee defined these events as a code blue resuscitation for cardiac arrest. Cardiac arrest was selected as a performance measure based on the literature, in which other studies found that increased recognition and earlier notification of clinical deterioration decreased in-hospital cardiac arrests

(Bingham et al., 2018; Nallamothu et al., 2018; Subbe et al., 2017). There was a rise in cardiac arrests from 60 in 2018 to 80 in 2019. Of the 80 cardiac arrests in 2019, 46% (37) were outside the ICU setting.

Additional outcome data included the number of rapid responses pre- and post-implementation. The number of rapid responses had decreased by 55% in the previous years, from 648 in 2018 to 356 in 2019. The organization's RRT policy defines rapid response events as events in which a patient needs immediate assessment or intervention. Before the project intervention rapid response events were only initiated by staff members. Therefore, the impact AI-automated notifications would have on staff-initiated RRT activations was measured. Additionally, based on the previous research findings, there was an anticipated increase in the number for rapid responses with the increased recognition and automated notification (Subbe et al. 2017; Wakeam et al., 2014).

Using Lippitt's Phase 6 and the i-PARHIS outer context focus area (Kitson & Harvey, 2016; Mitchell, 2013) from the project's conceptual framework to guide implementation, the iterative change management PDSA process was used. This change management process had not been used for previous changes to the organization's RRS. It was selected for this project because it allowed the team to test changes to the RRS as they were implemented and make any needed adjustments.

Source of Data

Most project data collection was through a retrospective chart review of the EHR and included data from the CPR committee on the number for cardiac arrests and rapid responses. The organization's CPR committee collects data on the number of cardiac arrests and rapid responses from multiple sources: the code blue documentation worksheets reviewed during the data abstraction process, quality review reports, and the hospital operator's overhead page log. The CPR committee chair cross-checks all the cases from the various inputs to determine the absolute number of cardiac arrests and rapid responses that occurred that month. Information on the impact on the RRS was collected from the team through the PDSA process. Further, a web-based survey tool was used to collect RRT nurse self-assessments on adherence to the new standard workflow processes.

Data Collection Instruments

Outcome data collected from the CPR committee on the number of cardiac arrests outside the ICU setting and rapid responses were maintained in an Excel spreadsheet (see Appendix P). The IT team developed a tracking report within the EHR system that recorded the automated AI notifications. The EHR report included details on the date and time of notification, patient name, location, and trigger source for notification. Qualitative data documented on the PDSA worksheet included project team feedback and findings throughout the implementation cycles (see Appendix Q). The web-based survey tool was used to collect data on adopting the new standard workflows, including questions related to adherence to the three main rapid response nurse workflows: change of shift review, AI-driven RRT notifications during the shift, and staff-initiated RRT activations during the shift.

Analysis

Quantitative Data

The project outcome measures were reviewed to determine if the addition of AI-automated RRT notifications improved clinical outcomes at the target organization. Project data presented in a bar graph format display the number of cardiac arrests outside the ICU, the total number of rapid responses pre- and post-intervention, and individual hospital campus (see

Appendix R, Figure 1 and Figure 2). Since the post-intervention data are from February through July 2020, the previous year's corresponding months were used for pre-intervention comparison.

Qualitative Data

Throughout the PDSA implementation process, the number of AI notifications was monitored and used to determine if the criteria were set at a meaningful sensitivity (see Appendix S). This iterative process made adjustments to the notification thresholds, starting with a conservatively low value high threshold score and gradually increasing. Based on other organizations' experiences, and as the notification threshold trigger point increased, the team decided to add notification criteria for significant increases in the AI score between filing periods. As well, exclusionary criteria and notification suppression rules were determined during the PDSA cycle implementation.

Adopting the new RRT nurse workflows was monitored during PDSA cycles two, three, and four via a self-assessment tool completed at the end of each RRT nurse shift (see Appendix T). The new RRT nurse change of shift and staff-initiated rapid response workflows had the most consistent compliance. However, the new workflow for an AI-initiated rapid response varied related to the follow-up EHR documentation and incidence reporting. After further exploration in the project workgroup meetings with the RRT nurses, it was identified that not all AI-notifications resulted in an AI-initiated rapid response. Therefore, not all AI-notifications required the same level of EHR documentation nor incidence reporting.

Ethical Considerations

The project aimed to improve the quality of the organization's rapid response procedure through enhanced recognition of patient deterioration. This aim was planned to be achieved by implementing AI into the existing EHR to recognize and notify the RRT nurse and unit charge nurses of patient deterioration. Designed as a quality improvement project, all patients received standard care, and the project did not override any clinical decision-making. This project was not intended to test a new intervention; it was to implement care practices based on evidence. This project was reviewed and approved by the organization's Nursing Research Council as quality improvement. Institutional Review Board (IRB): This is a quality improvement project and does not require IRB approval for implementation. The project has been evaluated and approved as a quality improvement initiative through the University of San Francisco School of Nursing and Health Professionals (see Appendix U).

The detailed patient outcomes related to cardiac arrests and rapid responses were collected and processed by a quality review coordinator to maintain patient privacy. The DNP student received only the de-identified outcome measure performance results.

The psychological wellbeing of the RRT members during this practice change project was assessed and addressed throughout the PDSA process: first, by recruiting RRT representatives to join the team during the planning stage; then, by eliciting their participation in the design of the intervention and testing; and finally, after implementation, by maintaining ongoing and frequent communication with the RRT members and other stakeholders on the practice change and making any needed adjustments.

The American Nurses Association's Code of Ethics Provision 4 states, "The nurse has the authority, accountability, and responsibility for nursing practice; makes decisions and takes actions consistent with the obligation to promote health and to provide optimal care" (Fowler, 2015, p. 191). Specifically, Section 4.2 Accountability for Nursing Judgments, Decisions, and Actions, states, "Systems and technologies that assist with clinical practice are adjunct to, not replacements for, the nurse's knowledge and skill" (Fowler, 2015, p. 191). This project addressed this ethical concern by retaining the nursing staff's autonomy to initiate a rapid response and implementing the AI only as a supplemental tool to RRT activation. The nursing staff continued to go to the bedside and assess the patient to determine the next steps.

This project reflected the Jesuit values of the University of San Francisco (USF, 2019) by aligning with the *people for others* value by improving the quality outcomes of rapid responses further and, thereby, reducing harm. In summary, there were no ethical concerns related to the implementation of this project.

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Section IV: Results

Cardiac Arrests

There were nine cardiac arrests outside the ICU during the 125 days the AI-automated notifications were on (February 4 to February 27, 2020, and April 20 through July 2020); seven at the larger Mountain View campus and two at the Los Gatos campus. Compared to February through July 2019 (181 days), pre-intervention with no AI-notification there were 13 cardiac arrests, 12 at the Mountain View campus and one at the Los Gatos campus. Therefore, the cardiac arrest rate pre- and post-intervention remained the same at 7.2%. While there is no statistically significant change, the decrease in the number of cardiac arrests shows that when AI is utilized, it is trending in the correct direction and aligns with the research findings on AI automation decreasing cardiac arrest (Churpek et al., 2016). With more time and data as we continue to improve AI implementation, we can better understand the true effect (see Appendix S).

Rapid Responses

There was a total of 188 staff-initiated rapid responses from February through July 2019, compared to 156 from February through July 2020. Since there was a break in the PDSA cycles due to the COVID-19 pandemic, the AI-automated notifications were turned off for 56 days, so the post-intervention rate was calculated based on the 125 days the AI was on. The pre-intervention rate was based on 181 days. The per-day average number of staff-initiated rapid responses pre-intervention was 1.04 and post-intervention was 1.25. This change was an increase of 20% in the average number of rapid responses per day. The average number of AI notifications per day varied during the PDSA cycles, running as low as 6.4 during PDSA cycle 2 and as high as 21.67 during PDSA cycle 3. Overall, there was an average of 12.43 AI notifications per day. The 20% increase in rapid responses was an expected outcome and was supported by the evidence, in which researchers found that an increase in staff recognition of clinical deterioration resulted in an increase of nursing staff alerting RRTs (Subbe et al. 2017; Wakeam et al., 2014). While the AI-notifications alerted the RRT nurse and charge nurses to changes in patient conditions, the increase in rapid responses may also have resulted from the communication and educational efforts related to implementing the deterioration index AI module.

PDSA Cycles

PDSA cycle one was February 4 to February 27, during which time there were no cardiac arrests outside the ICU setting, 27 staff-initiated rapid responses (0.89 per day), and 270 AI notifications (11.73 per day). At the end of this PDSA cycle, the team noted that the high-risk threshold score of 60 might have been too sensitive and was inappropriately triggering alerts. The team chose to make three changes to the notification logic to reduce the risk of alert fatigue:

1. The high-risk threshold notification criterion was increased from a deterioration index value of 60 to 62 to reduce high-risk threshold notifications.
2. Based on another organization's alert logic to notify the RRT nurses of patients with sudden increases in their deterioration index score, a new notification criterion would be added to send the RRT nurse a notification if the patient's score increased 15 or more within 35 minutes.
3. To further eliminate notifications on patients actively dying, patients admitted to general inpatient hospice would be excluded from the alert logic.

In this PDSA cycle, the final display settings in the EHR were also defined. The team acknowledged that although a standard workflow process for incorporating the AI into the RRS had been defined, there was inconsistency in following the new workflow. Therefore, a fourth change was developed, a web-based self-assessment tool for the RRT nurses for the upcoming PDSA cycles.

PDSA cycle two was from April 20 to May 5. There was one cardiac arrest outside the ICU setting, 13 staff-initiated rapid responses (0.81 per day), and 97 AI notifications (6.46 per day). At the time of this PDSA cycle, the organization had a dramatic drop in patient volume related to the COVID-19 pandemic and cancelation of elective procedures. This decreased volume helped to uncover an issue with AI notifications on discharged patients. Therefore, the team agreed for the next PDSA cycle to modify the AI notification logic to exclude discharged patients. The team also noted unnecessary AI notifications for patients undergoing procedures, so a rule to exclude them was added to the notification logic. The team expressed concerns that the criteria for sudden changes to a patient's deterioration index score were not sensitive enough, so it was decided to decrease the notification criteria from an increase of 15 to 10 points. During this PDSA cycle, the RRT nurses noted several AI notifications for inaccurate Glasgow coma scale assessments, late or inaccurate documentation. Educational reminders were sent out to the involved units on the need for timely and accurate documentation, and RRT nurses gave one-on-one coaching to nurses who inaccurately documented Glasgow coma scale assessments to reduce these inaccurate AI notifications.

PDSA cycle three was from May 6 to May 14. There were two cardiac arrests outside the ICU setting, eight staff-initiated rapid responses (0.89 per day), and 195 AI notifications (22 per day). The RRT nurses reported that the automated notification logic was too sensitive, identifying patients not showing signs of clinical deterioration and that the number of AI notifications per day was too difficult to manage. Based on this feedback and to address alert fatigue concerns, the team chose to adjust the AI score for the high-risk threshold notifications from 62 to a score of 65. Additionally, they decided to adjust the notification criteria to increase the AI score within 35 minutes from 10 points to 13 points.

PDSA cycle four was May 15 to May 25, during which time there were no cardiac arrests outside the ICU setting, seven staff-initiated rapid responses (0.7 per day), and 154 AI notifications (15.4 per day). Nearly half of the AI notifications were for patients in the progressive care unit (PCU), the highest acuity unit included in the intervention. Many of these patients were noted to have DNR code status orders, without additional orders or goals of care documented to limit rapid response team interventions should the patient's condition deteriorate. The automated notification logic was designed to suppress notifications for eight hours after the RRT nurse evaluated the patient's condition, and the patient's AI score was marked as reviewed within the EHR. To reduce the risk of alert fatigue from notifications on DNR patients, the team chose to add a 24-hour suppression rule to the notification logic. The team noted that there were times in which the RRT nurse was delayed in responding to AI notifications, so the team agreed to expand which nurses would receive AI notifications via the organization's wearable device to include the unit charge nurses. This change supported increased recognition of patient deterioration and aligned with the staff-initiated RRT notification process.

PDSA cycle five was from May 26 to July 12. There were three cardiac arrests outside the ICU setting, 16 staff-initiated rapid responses (0.88 per day), and 231 AI notifications (12.83 per day). To reduce the workload on the RRT nurses for PCU patients with sustained high AI scores, the team decided to educate the PCU charge nurses on the workflow to evaluate the patient's condition and *marked as reviewed* in the EHR. In cycle five, during the team meetings, the results from the standard workflow self-assessments were reviewed, and changes were incorporated into the final workflows, which ended the self-assessment evaluative period. Lastly, the RRT nurses reported that some AI notifications had been missed due to the alert tone of a new text message to the wearable device being too quiet in some settings. Therefore, the team lead worked with IT and the wearable device vendor to change the AI notifications from a text message to an automated text to speech format.

Standard Workflow

The standard work, web-based, self-assessment tool was used during PDSA cycles two, three, and four to monitor adoption and adherence to the standard work developed to incorporate the AI into the RRS. The RRT nurses were instructed to complete a self-assessment at the end of each shift. Eighty-nine self-assessments were completed, which was approximately 41% of the survey period's RRT nurse shifts. The self-assessment questions were divided into the three workflows and designed for the RRT nurse to confirm *yes* or *no* on whether they had followed each standard work step. All 89 nurses surveyed responded to the first three questions. There was also a fourth question on response time to each type of RRT.

The question "I followed the standard work process for change of shift" resulted in nearly all surveyed indicating that they reviewed the AI patient list with the off-going staff member (96.63%), but only 88.76% sorted the list by the highest AI score, and only 78.65% reviewed each patient whose score was over the high-risk threshold value of 62. Reasons noted in the comments for not completing the steps included no patients on the list with high-risk AI score, another alert event at the change of shift, and patients already known.

In response to the question "I followed the standard work process for DI Alert During Shift," the majority surveyed completed the steps related to reviewing the patient's EHR

(85.39%), contacting the primary nurse (74.16%), and updating DI patient list with a note and checking *mark as reviewed* (76.14%).

However, because many responded *no DI alerts during the shift*, only 11.24% of the AI notifications resulted in activation of the RRT. Only 34.48% responded that they documented interventions in the patient record. Only 2.27% completed a rapid response critique.

In response to the question “I followed the standard work process for Rapid Response Alert,” the majority indicated there was no rapid response on their shift (87.64%). Of the nine survey respondents who did note responding to an RRT on their shift (10.11%), all documented in the Rapid Response Narrator in the EHR, but only eight completed an RRT critique. Even though only nine answered that they had responded to an RRT, 21 respondents (25.61%) answered that they did update the DI patient list with a note and by checking *mark as reviewed*.

Lastly, 72 replied to the question “My response time was.” The response times of five staff were that they had responded to staff-initiated rapid responses within five minutes 80% of the time, and only one time was it reported that the RRT nurse responded in 15 to 30 minutes. However, for the 88 AI notifications, there was more variation in response time: 28 (32%) were responded to in zero to five minutes, 33 (38%) in five to 15 minutes, 13 (15%) in 15 to 30 minutes, and 14 (16%) took more than 30 minutes to respond. Barriers to response times noted in the comments included busy with other patient care at the time of the alert, consecutive AI notifications, and missed hearing wearable device notification.

Section V: Discussion

Summary

Current early warning systems are not sufficient and reliable as a tool for recognition of patient deterioration. However, with the development and adoption of EHRs, hospitals have more data than ever to use. Unlike early warning systems that use limited data from a single point in time, AI machine learning systems use regression logic to analyze current and historical patient data to predict patient deterioration more reliably and accurately. Hillman, Lilford, and Braithwaite (2014) stated that RRSs need to evolve to improve patient safety further. Some hospitals have already successfully done this and implemented AI into their RRSs. In 2017, Ochsner Health announced its remarkable reduction of codes outside the ICU by 44% after implementing an AI-driven prediction tool based on Epic's machine learning tools (Ho, 2018). Since then, Epic has continued to develop its machine learning platform, using data from over 125,000 hospitalized patients (Milani, 2018). This evidence supported the project aim to implement Epic's deterioration index AI module into the organization's well-established, staff-driven RRS to increase earlier identification, notification, and intervention to improve clinical outcomes and reduce cardiac arrest.

Using the PDSA process, the project achieved the goal of incorporating AI-initiated rapid response notifications into its RRS. While not creating enough data to determine if improvements were statistically significant the aim to reduce cardiac arrests outside the ICU, suggests that the data is trending positively. Additionally, using the existing AI software available in the organization's EHR, the project was highly cost-effective, and was relatively easy to implement into the established RRS.

One of the most valuable lessons learned during this project was the importance of establishing and monitoring adherence to the standard workflow processes. RRT nurses work independently during their shifts, so previous deviations in practice may have been more acceptable. However, integration of AI notification criteria into the RRS relies on the RRT nurse interacting with the EHR; the entire RRT nurses' team must consistently follow the workflow practices. Another factor contributing to this project's success was partnering with the organization's IT team. The IT team members were able to make timely adjustments to the AI notification system, and they contributed significantly to the understanding of the AI module and design of the AI notification logic, inclusion, and exclusion criteria. The dissemination plan will be to share the project details and outcomes widely within the organization, eventually reaching outside of the organization to compare implementation and clinical outcome findings directly with other Epic sites and at larger regional or national conferences.

Interpretation

The project results indicate that the addition of AI technology stimulates earlier engagement of rapid response nurses and decreases in-hospital cardiac arrests outside the ICU. The research indicates that earlier activation of RRTs through an automated alert system based on AI would decrease in-hospital cardiac arrests. Future utilization of AI technology to support faster, more reliable clinical warnings should be considered.

Limitations

This project's potential limitations include the documentation timeliness and its impact on the AI notifying the RRT. These limitations were addressed during the implementation process by adding education on the importance of timely documentation to support patient safety.

Results may have been impacted by a change in the organization's code status policy. In January 2020, the options were reduced from full code, limited code, DNR, and DNR comfort care to only full code and DNR. This policy change may have led to an increase in the number of patients with the code status order for DNR, which may have skewed the results related to the number of cardiac arrest code blues.

Lastly, the project implementation and outcomes were likely impacted by the COVID-19 pandemic. Due to the pandemic's onset, there was nearly an eight-week break between PDSA cycle one and cycle two. Additionally, the organization's inpatient admission volume and the number of elective procedures dropped drastically.

Conclusions

In reviewing the literature related to the PICOT question, the evidence indicates that earlier activation of RRTs through an automated alert system based on AI technology would decrease in-hospital cardiac arrests outside the ICU. The evidence describes characteristics of robust RRSs and barriers to activation, which was useful because the organization had an established nurse-driven activation. Based on this evidence, the practice change of supplementing nurse-driven rapid response activation with automation has likely improved clinical outcomes.

Based on the findings from the literature and the quality and safety education for nurse competencies (Cronenwett et al., 2007), the executive nurse leader's recommended action is to incorporate an AI-based trigger tool into the RRT activation procedure. Doing so will further promote safe patient care and facilitate the leveraging of technologies that support effective systems and performance to minimize patient harm. The executive nurse leader uses data, such as the number of cardiac arrests outside the ICU setting and rapid responses, monitoring care process outcomes, and using quality improvement tools, like the PDSA tool, to lead the continuous improvement of earlier recognition intervention at the intra- and inter-professional level.

Section VI: Other Information

Funding

This DNP project had no outside funding.

Section VII: References

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Section VIII: Appendices

Appendix A

Evidence Evaluation Table

PICOT question: In adult inpatients (P), how does implementation of an artificial intelligence based automated early warning system (I) compared to nurse-driven activation of rapid response (C) effect in-hospital cardiac arrests (O) over a six-month period (T)?

Article #	Author and Date	Evidence Type	Sample, Sample Size, Setting	Findings That Help Answer EBP Question	Observable Measures	Limitations	Evidence Level, Quality
1	Gao et al., 2007	Systematic review	36 papers	Review of track and trigger tools used / developed by hospitals to activate rapid response teams.	Hospital-developed track and trigger tools used to identity patients at risk for deterioration - not reliable	None of the studies meet quality standards for methods	Level I Systematic review Good quality
2	Lyons et al., 2018	Systematic review	N/A	Review of rapid response systems. Human factors, technology, future.	Future direction	Other factors decrease code events	Level I Literature review Good
3	Winters et al., 2013	Systematic review	18 high-quality meta-analysis and 26 lower quality studies reviewed	A review of 18 studies on the pros and cons of rapid response systems. Findings include need to automate notifications of deteriorating patients.	Rapid response systems shown to have moderately improved outcomes	Review included studies of low to moderate quality and sample sizes varied in the various studies.	Level I High quality Systematic review
4	Angel, 2016	Quantitative	All adult cardiac arrests over 3 years, 273 patients	Early interventions by well-functioning RRT could decrease cardiac arrests.	Decrease mortality, reduced LOS in CCU post arrest	Sample size	Level III Retrospective cohort study Good
5	Churpek et al., 2012	Quantitative	47,427 patients over 27 months	CART (early warning tool) predicted cardiac arrest better than MEWS.	Rate of cardiac arrest	1. Single center study 2. CART vs MEWs	Level III Retrospective cohort study Good

6	Churpek et al., 2016	Quantitative	Five hospitals, over 5 years, all hospitalized ward patients	Found that several machine learning methods more accurately predicted clinical deterioration than logistic regression. Use of detection algorithms derived from these techniques may result in improved identification of critically ill patients on the wards.	1. Number of cardiac arrests 2. Number of transfers to ICU	1. Only 5 hospitals in one state 2. Did not compare all available methods or their variations	Level III Observational cohort study High
7	Subbe et al. 2017	Quantitative	2,139 patients over 1 year	Increase rapid responses, decrease cardiac arrests, and decrease mortality of select patients.	Number of serious events	During intervention period increase communication	Level III High
8	Astroth et al., 2017	Mixed quantitative & qualitative	202 RNs	Developed a possible scale to identify barriers for RRT teams.	Relationship between 25 different track and trigger tools	Lower subject rates	Level III Exploratory High
9	Astroth et al., 2013	Qualitative	15 nurses, 1 hospital	Identify barriers to calling rapid responses.	1. RRT characteristics 2. Unit culture	Sample size	Level III High
10	Wakeam et al., 2014	Qualitative, nonexperimental	7 hospitals, 106 interviews	Describes that hospitals leveraging data in EHR to identify trends and recognize clinical deterioration sooner.	Identified barriers and strategies to improve failure to rescue	Possible bias because TJC conducting study	Level III High Quality Good quality
11	Rojas et al., 2017	Opinion of nationally recognized experts based on experimental evidence	14 sessions	Discusses future use of machine learning to automate rapid response activation.	N/A	None identified	Level V Conference Summary High quality

Appendix B

Conceptual Framework

Nursing Process	**Lippitt's Theory**	**i-PARIHS**
Assessment	Phase 1: Diagnose the problem	Characteristics of the innovation
	Phase 2: Assess motivation and capacity for change	Recipients
	Phase 3: Assess change agent's motivation and resources	
Planning	Phase 4: Select progressive change object	Inner context: local level
	Phase 5: Choose appropriate role of the change agent	Inner context: organizational level
Implementation	Phase 6: Maintain change	Outer context
Evaluation	Phase 7: Terminate the helping relationship	

Appendix C

Letter of Support from Organization

El Camino Health

Hospital Campuses

2500 Grant Road
Mountain View, CA 94040
650-940-7000

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Los Gatos, CA 95032
408-378-6131

elcaminohealth.org

September 14, 2019

University of San Francisco, School of Nursing
2130 Fulton Street
San Francisco, CA 94117-1080

To whom it may concern:

I am writing this to express my support of Alicia Potolsky, RN, MSN, BC-NE, to implement her Doctor of Nursing Practice Comprehensive Project at El Camino Health. Her project scope will be to implement Epic's machine learning module, Deterioration Index, to enhance the rapid response system at El Camino Health's hospitals in Mountain View and Los Gatos.

We give her permission to use the name of our organization in her Comprehensive Project Paper and future publications and presentations. This letter also verifies that El Camino Health has an existing contract with the University of San Francisco's School of Nursing.

Sincerely,

Cheryl Reinking, RN, MS, NEA-BC
Chief Nursing Officer
2500 Grant Road, Mountain View, CA 94040
650-940-7121 Direct
cheryl_reinking@elcaminohealth.org
elcaminohealth.org

Appendix D

Project Charter

El Camino Health **Project: Deterioration Index**

Project Charter: Deterioration Index

Date	July 30, 2019
Project Name	Deterioration Index
Project Facilitator	Alicia Potolsky, MSN, RN, NE-BC, Director Critical Care Services
Department & Extension	Patient Care Services, 650-940-7139
Executive Sponsor(s)	Cheryl Reinking, CNO; Deb Muro, CIO; and Dr. Mark Adams, CMO
Goal to Achieve	The project aim is to reduce in-hospital cardiac arrests through the implementation of artificial intelligence (AI) into the existing electronic health record (EHR) in order to recognize and notify the rapid response team of patient deterioration sooner. The proposed project is to implement Epic's machine learning Deterioration Index module into the El Camino Hospital's EHR (iCare). Using the plan-do-study-act (PDSA) quality improvement process, the project will integrate automated alerting into the established rapid response system to increase earlier recognition, notification, and intervention of patient deterioration and therefore reduce in-hospital cardiac arrests.
Current Situation	El Camino Hospital implemented the rapid response team model in January 2006, in which any hospital staff could activate the rapid response alert if a patient met any of the defined clinical criteria, or if the staff had concerns about the patient's clinical presentation. In November 2015, with the implementation of Epic, the RRT nurses were taught to use the embedded medical early warning score (MEWS) to assess for deterioration proactively. However, because MEWS does not reliably and accurately identify patients at risk for deterioration, the tool has not been incorporated into the RRT nurses' practice. The CPR Committee monitors the number of code blues and rapid responses for the entire organization. Between January 1 to December 31, 2018, there were 58 in-hospital code blues for cardiac arrest, 648 rapid response alerts, and 120 transfers to a higher level of care.
Reasons	1. Current MEWS is not sufficient and reliable as a tool for recognition of patient deterioration. 2. Artificial intelligence machine learning systems use regression logic to analyze current and historical patient data to more reliably and accurately predict patient deterioration. 3. In 2017, Ochsner Health had a reduction of codes outside the ICU by 44% after implementing an artificial intelligence-driven prediction

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El Camino Health **Project: Deterioration Index**

	tool based off of Epic's machine learning tools. Since then, Epic has continued to develop its machine learning platform, using data from over 125,000 hospitalized patients (i.e. it's even better). 4. To reduce the number of cardiac arrests (which would have a positive impact on hospital mortality index, which aligns with strategic goal).
Alternatives/Options	• Option 1 – Implement Epic's Deterioration Index into hospital's EHR to supplement RRT activation process. • Option 2 – Continue with same staff-driven only RRT activation model.
Impact of Doing Project	• Project - The main objective of this project will be to form a team to implement Epic's Deterioration Index into the hospital's rapid response procedure, which will include the use of AI technology to augment RRT activation. The project's expected outcomes are to; increase the number of rapid responses, decrease the number of in-hospital cardiac arrests, and decrease in transfer to a higher level of care. • Option 1 – Require time from Information Systems (IS), iCare, Nursing (leaders and RRT RNs), Respiratory Therapy, Clinical Education, and Quality Abstractor to participate and support project. • Option 2 – Status quo.
Impact of Not Doing Project	The impact of not doing the project will be continued reliance on staff to recognize and activate RRT.
Human Resources	Project resources: • Clinical leaders from Nursing (MV & LG) and Respiratory Therapy • Rapid Response Team member representatives • Clinical Education to lead communication and education • Quality Abstractor to collect and help analyze outcome measures These resources will be able to maintain their commitment to the project while working in their primary role. The impact to time will be less than 3 hour each month during the planning and implementation phases; then it anticipated to reduce down to 1 to 2 hours per month.
Technical Resources	• iCare analysts(s) to build/install Deterioration Index and build BPA • Report writer to create needed reports for monitoring, • Information Systems (IS) analyst to build alert integration to Vocera

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El Camino Health **Project: Deterioration Index**

Project Dependencies	• Time availability of persons identified to participate in project. • Policy revisions completed and approved timely. • Capability of iCare and Vocera integration. • Differences in RRT make up between the two campuses.
Desired Completion Date	Go-Live: Target October 2019 (prior to 'flu' season)
Evaluation Metrics	• Number of Cardiac Arrests (code blues) • Number of Rapid Responses • Number of transfers to higher level of care • Mortality Index

Project Initiation Signoff: *(Please Prioritize, Sign and Date to Authorize Project to Begin)*

Project Priority:	High

Date: 7/30/2019	**Project Facilitator:** Alicia Potolsky Alicia Potolsky
Date: 7/31/2019	**Executive Sponsor:** Cheryl Reinking (approved via e-mail)

Deborah Muro 8/23/19

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Appendix E

Standard Process Description

Standard Process Description: DI-Rapid Response Workflows

Process Description:

- The RRT RN will monitor, assess, intervene as needed and document on all patients over 18 years of age with a Deterioration Index (DI) score greater than or equal to 65 or if there is an increase of 13 points within 35 minutes.
- The DI Alert will NOT fire for ED, OR/CCL, CCU/ICU, Peri-Op, Comfort Care, GIP, or discharged patients.
- The DI Alert will NOT fire for 8 hours after 'Mark as review' on DI Patient List.
- The DI Alert will NOT fire for 24 hours after 'Mark as review' on DI Patient List for patients with active DNR order.

Who Must Use this Process?

- Flex RN, RRT RN, LG-ICU Charge RNs

Process Notes:

- The DI-RRT Vocera alert is intended to streamline notification of the rapid response team of patient deterioration.

Process Requirements:

- Flex RN, ICU Charge RNs need to be logged into Vocera and in group "Flex RN"
- Charge RNs need to be logged into Vocera and in group "Charge RN"

Process and Detailed Steps

Process Step (in sequence)	Detailed Steps (in sequence)	Cycle Time	Visual
Change of Shift	1. At the start of shift the off-going RRT RN will review the **DI Patient List** with the on-coming RRT RN. 2. Sorting patient list by highest DI score to lowest. 3. Review each patient with score of 65 or greater. 4. Review patients who were a DI alert during the previous shift.	5-10 minutes	DI Patient List is a shared list in Epic.
DI-RRT During Shift	1. Rapid Response Team receives Vocera AI-RRT text alert of DI score greater than or equal to 65 or jump in score greater than 13. 2. Rapid Response RN reviews patient's score contributors via the DI patient list. 3. Rapid Response RN reviews patient's DI trend graph via Deterioration Accordion view. 4. Rapid Response RN then calls unit to speak with primary RN, and then respond accordingly. a. If indicated, call RRT (follow RRT workflow) b. If RRT is not indicated, place a note in 'Marked as Reviewed' column 5. If RRT is called, complete RRT critique as usual. 6. Document in patient record any interventions as usual. 7. After patient needs addressed, update the DI Patient list **'DI Time since Reviewed Column'** by selecting "Mark as Reviewed" with a brief standard note. 8. Document in the Rapid Response Narrator as usual. 9. Complete RRT Critique as usual.	20-40 minutes	

Rapid Response	1. Staff initiated Rapid Response Alert called via Vocera 2. Respond and perform per the Rapid Response Procedure. 3. Document in the Rapid Response Narrator as usual. 4. Complete RRT Critique as usual. 5. After patient needs addressed, update the **DI Patient List 'DI Time Since Reviewed Column'** by selecting "Mark as Reviewed" with a brief standard note. *Example: "RRT called, see Rapid Response Code Timeline"*	Time varies on situation	Notes entered on **'DI Time Since Reviewed Column'** are not part of medical record, are not stored. This is a single note that can be accessed and updated multiple times.

Appendix F

Gap Analysis

Appendix G

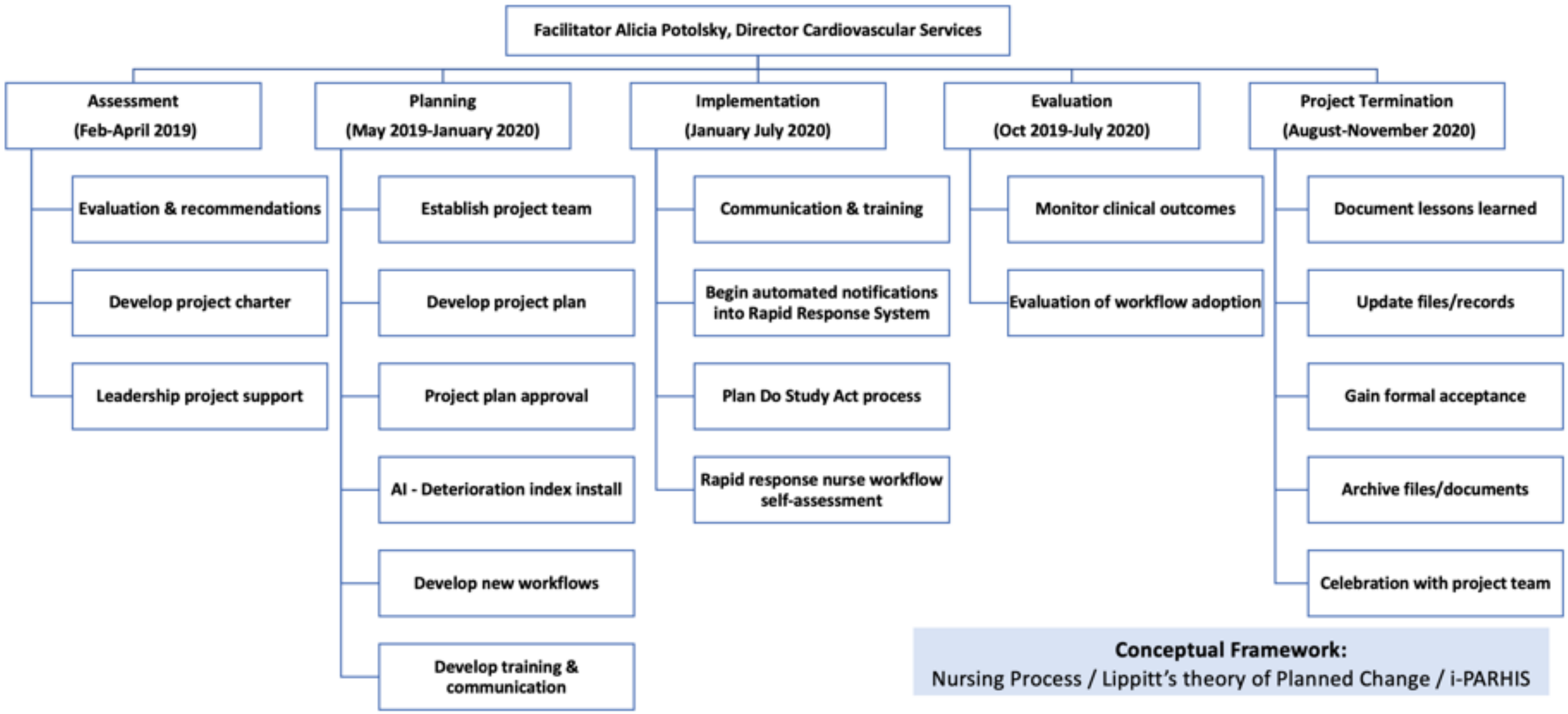
Gantt Chart

WBS	Task	Feb-19	Mar-19	Apr-19	May-19	Jun-19	Jul-19	Aug-19	Sep-19	Oct-19	Nov-19	Dec-19
1	**<u>Assessment (Feb-April 2019)</u>**											
1.1	Evaluation & Recommendations											
1.1.1	Review the evidence											
1.1.2	Review current org performance											
1.1.3	Determine system feasibility											
1.2	Develop Project Charter											
1.3	Leadership Project Support											
1.3.1	Executive sponsorship											
1.3.2	High level clinical leadership engagement											
2	**<u>Planning (May 2019-January 2020)</u>**											
2.1	Establish Project Team											
2.1.1	Determine Project Team											
2.1.2	Project Team Kickoff Meeting											
2.1.3	Establish Workgroup meetings											
2.2	Develop Project Plan											
2.2.1	Define KPIs											
2.3	Project Scope Statement											
2.4	Milestone: Project Plan Approval											
2.4.1	Project Kickoff Communication											
2.5	Deterioration Index Install											
2.5.1	Procure AI Software											
2.5.2	Install AI into EHR system											
2.5.3	AI Maturation Period											
2.5.4	Functional Testing Phase											
2.5.5	Retrospective Analysis											
2.5.6	End user design											
2.6	Develop new workflows											
2.7	Develop Training & Communication											

WBS	Task	Jan-20	Feb-20	Mar-20	Apr-20	May-20	Jun-20	Jul-20	Aug-20	Sep-20	Oct-20	Nov-20
2.7	Develop Training & Communication											
3	**Implementation (January-July 2020)**											
3.1	Communication & training											
3.2	Begin automated notifications into Rapid Response System											
3.3	Plan Do Study Act process											
3.4	Rapid Response nurse workflow self-assessment											
4	**Evaluation (February-August 2020)**											
4.1	Monitor clinical outcomes											
4.2	Evaluation of workflow adoption											
5	**Project Termination (August-November 2020)**											
5.1	Document Lessons Learned											
5.2	Update Files/Records											
5.3	Gain Formal Acceptance											
5.4	Archive Files/Documents											
5.5	Celebration with Project team											

Appendix H

Work Breakdown Structure



Appendix I

SWOT Analysis

	Strengths	**Weaknesses**

Internal	• Organization on Epic
	• Access to Epic resources
	• Established Rapid Response Team & Policy
	• Aligns with
	  o Org value, 'to embrace solutions and forward-thinking approaches that lead to better health'
	  o strategic goals to reduce mortality
	  o HVI goal to reduce cardiac arrest
		• Organization has many projects and priorities
		• IT has limited resources / capability
		• Securing time commitment and participation of stakeholders
		• Resistance to change
		• Mistrust of AI

	Opportunities	**Threats**
External	• RRT RNs not using embedded tool MEWS consistently to identify patient deterioration • MEWS not consistently reliable or accurate in identifying at risk patients. • RRT activation is dependent on nurse action.	• Relying on other organizations and/or Epic to share AI technology • Physician engagement and acceptance

Appendix J

Budget

	Number of Employees	Est. Average Hourly Rate	Total Hours	Total Cost + 33% benefits
Project Team:				
Executive Sponsors	2	$ 250.00	4.5	$ 1,496
Directors				
Cardiovascular Services	1	$ 101.61	144	$ 19,460
Other Nursing Directors	3	$ 101.61	18	$ 2,433
Respiratory Therapy	1	$ 53.04	6	$ 463
Managers				
Patient Care Resources	1	$ 89.00	10	$ 1,184
Clinical Applications	1	$ 101.61	120	$ 1,351
Educators	2	$ 84.48	20	$ 2,247
IT Analysts	2	$ 71.63	120	$ 11,433
Rapid Response RNs	5	$ 80.45	180	$ 19,260
Rapid Response RTs	1	$ 37.34	9	$ 447
Quality Analyst RN	1	$ 60.77	10	$ 808
Total				$ 60,582
Contingency (10%)				$ 6,058
			Total Cost	**$ 66,640**

Appendix K

Cost/Benefit Analysis

Return on Investment = $578,765 / $98,862 = 5.85

Assessment, Planning, Implementation		Evaluation and Project Termination			
Expenditures	**Total Cost Start Up (2020)**	**Year 1 3% Inflation (2021)**	**Year 2 3% Inflation (2022)**	**Year 3 3% Inflation (2023)**	**Total Costs**
Executive Sponsors	$1,496	$257	$265	$272	$2,290
Directors					
Cardiovascular Services	$19,460	$835	$860	$886	$22,042
Patient Care Resources	$811	$139	$143	$148	$1,241
Los Gatos Nursing	$811	$-	$-	$-	$811
Respiratory Therapy	$463	$-	$-	$-	$463
Clinical Education	$811	$-	$-	$-	$811
Patient Care Resources	$1,184	$732	$753	$776	$3,445
Clinical Applications	$1,351	$835	$860	$886	$3,933
Educators	$2,247	$1,389	$1,430	$1,473	$6,540
I.T. Analysts	$11,433	$1,178	$1,213	$1,249	$15,073
Rapid Response RNs	$19,260	$3,306	$3,405	$3,508	$29,479
Rapid Response RTs	$447	$307	$316	$326	$1,396
Quality Analyst RN	$808	$499	$514	$530	$2,352
Total:	$60,582	$9,477	$9,761	$10,054	$89,875
Contingency (10%)	$6,058	$948	$976	$1,005	$8,987
Total Expenditures:	$66,640	$10,425	$10,737	$11,059	**$98,862**
Cost Savings	**Total Cost Savings Base Year (2020)**	**Year 1 3% Inflation (2021)**	**Year 2 3% Inflation (2022)**	**Year 3 3% Inflation (2023)**	**Total Cost Savings**
Estimated value of one year of life	$129,000	$132,870	$136,856	$140,962	$539,688
Resuscitation medications	$550	$567	$583	$601	$2,301
Resuscitation supplies	$615	$633	$652	$672	$2,573
Code team for 1 hr.	$896	$923	$950	$979	$3,747
Estimated cost of code	$2,061	$2,123	$2,186	$2,252	$8,621
Estimate 16 less codes per year:	$161,971	$166,830	$171,835	$176,990	**$677,627**
ROI	**1.43**	**15.00**	**15.00**	**15.00**	**5.85**

ROI = (Total Cost Savings - Total Expenditures) / Total Expenditures

Appendix L

Return on Investment Plan

Total average cost avoidance:	$161,971	
Total cost of implementation:	$66,640	
Year one net total savings:	$161,971 (Total average cost avoidance) - $66,640 (Total cost for implementation) =	$95,331
Return on investment (ROI):	(Total Cost Savings - Total Expenditures) / Total Expenditures $95,331 / $66,640 =	**ROI = 1.43**

Appendix M

Responsibility/Communication Matrix

Stakeholder	Objective	Timing	Format	Responsible
Chief Nursing Officer, Executive Sponsor	Inform on project status and communicate any barriers to project success that need executive level assistance.	Monthly	In-person meeting	DNP Student
Chief Information Officer	Gain approval and prioritization to implement Deterioration Index, as well as commitment of needed IT resources to build and support project.	Project initiation and as needed	In-person meeting	DNP Student
Chief Medical Officer	Gain approval of project to further support rapid response system as a quality improvement initiative.	Once	In-person meeting	DNP Student
Clinical Leadership	Inform of project status and gain needed support of staff time to participate in supporting project.	Project initiation then quarterly	In-person at leadership meetings	DNP Student
Medical Staff Leadership	Inform of project status and gain needed support of staff time to participate in supporting project.	Once	In-person at leadership meetings	DNP Student
Rapid Response Team Policy Owner	Inform of project status and discuss potential need to modify policy to reflect revised rapid response team activation process.	Project initiation and as needed	In-person at project meetings and via e-mail	DNP Student
Rapid Response Team	Inform of project and potential impact to rapid response team activation and number of code blues. Regularly communicate project progress.	Monthly	Once at in-person meeting, then via monthly project status update e-mails	DNP Student
Project Team	Regularly communicate project progress, meeting times, agendas, follow-up tasks and responsibilities.	Biweekly to monthly	In-person at project meetings and via e-mail	DNP Student
Clinical Education	Disseminate information on modified rapid response team activation process and policy.	Biweekly prior to activation	In-person at project meetings and via e-mail	DNP Student and Director of Clinical Education
CPR Committee	Inform of project status and potential impact to rapid response team activation and number for code blues.	Project initiation and as needed	In-person at CPR Committee meeting	DNP Student
Direct Care Nursing Leadership	Announce project, project aim, and gain direct care nursing support.	Project initiation and as needed	In-person at Central Partnership Council meeting	DNP Student

Stakeholder	Objective	Timing	Format	Responsible
Direct Care Nurses	Announce project, project aim, and educate on modified rapid response team activation process and policy.	Two weeks prior to activation	Newsletter, e-mail, flier, unit huddles	DNP Student, Clinical Education, Department Leadership
Medical Staff	Announce project, project aim, and educate on modified rapid response team activation process and policy.	Two weeks prior to activation	Newsletter	DNP Student, Medical Staff Office

Appendix N

Educational Communication for Rapid Response Team

Education Department

DI-Driven Rapid Response Workflow

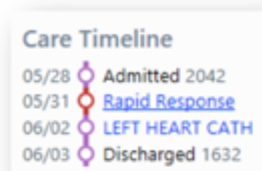
Standard Workflow for Rapid Response Nurse

Change of Shift – Review High Deterioration Index Patients

- Review the DI patient list with the on-coming Rapid Response RN.
- Review each patient with score of 65 or greater.
- Review patients who had a DI-RRT or staff initiated RRT during the previous shift.

DI-Driven Rapid Response

- Rapid Response RN & charge RNs will receive Vocera text DI-RRT message when DI scores greater than or equal to 65 or score increased by greater than 13 points or more in last 35 minutes.
- Rapid Response RN & unit charge RN, review patient's score contributors via the DI patient list and do a brief chart review.
- Rapid Response RN will contact primary RN for update and confirmation of patient status.
  - *If indicated, call RRT (follow RRT workflow)*
    - *If RRT is not indicated, place a note in 'Marked as Reviewed' column*
    - *If RRT is called, complete RRT critique as usual.*
- Document in patient record any interventions per Rapid Response Narrator. Note, using the narrator captures the Rapid Response in the Care Timeline for tracking purposes. Also, this creates a hyperlink to your Rapid Response documentation.
- After patient needs are addressed, update the DI Patient List with "Mark as Reviewed' with a brief standard note.
- Update 'Flex Nurse Shift Log' per policy including the DI Score (MV only).



Staff Driven Rapid Response

- Respond and perform per the RRT procedure.
- Document in the Rapid Response Narrator as usual.
- Complete RRT Critique as usual.
- After patient needs are addressed, update the DI Patient List in the **'DI Time Since Reviewed'** column by selecting 'Mark as Reviewed". Include a brief standard note - Example: '*RRT called, see Rapid Response Code Timeline'*.

07.03.2020

El Camino Health

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Appendix O

Educational Communication for Hospital and Medical Staff

Education Department

Effective July 13, 2020

'Staff – Initiated' versus 'DI – Initiated' RRTs

Reminder: The '**DI RRT**' (Deterioration Index-RRT) is based on what the Artificial Intelligence (AI) reads in Epic. This Artificial Intelligence calculates and analyzes your patient's condition, especially if your patient's condition is changing or begins to deteriorate.

Why use Epic's Artificial Intelligence? EPIC's Artificial Intelligence (AI) has the ability to continually analyze your patient's data. The AI will trigger the Deterioration Index and will activate an RRT if your patient's data reflects deterioration in your patient's condition. The Artificial Intelligence will always monitor your patient; thereby, will reduce mortality and will decrease the possibility of a cardiac arrest.

What does this mean?
'Staff–Initiated RRT' - NO CHANGE in this process. When you are concerned with changes or notes deterioration in your patients, you will continue to call an RRT.

'DI–Initiated RRT' - When a patient's condition changes or is deteriorating, the AI will detect the changes and will automatically trigger the **Rapid Response Nurse** and the **Charge Nurse Group.**

How does this work?
The DI–Initiated RRT is sent via Vocera with a notification beep and text message. This message will go to the **RRT nurse** and to the **Charge Nurse Group** with the patient's room number on the Vocera display window. The RRT nurse and the Charge Nurse will contact the patient's primary nurse, review the patient's chart and check on the patient.

Which patients will be monitored by the Artificial intelligence?
All admitted patients 18 years and older on the following units:

- MV – 2C, 3A (PCU), 3B, 3C, 4A, 4B, L&D, MBU, MHAS
- LG – Med-Surg/Ortho, Rehab, L&D, MBU
- Patients **not** monitored by AI: ED, OR, Cath Lab, CCU/ICU or patients with Comfort Care Orders/GIP

What is the Artificial Intelligence looking at and calculating?
Age, systolic BP, temp, pulse, RR, SpO2, Glasgow Coma Scale, abnormal neurological assessment, hematocrit, WBC count, K+, Na, abnormal platelets, abnormal BUN, blood pH, and abnormal cardiac rhythm.

Where is the Deterioration Index in Epic? *See back page*

Documentation matters! Chart timely and accurately!

El Camino Health

Questions? Contact your Manager and/or Educator.

2500 Grant Road | Mountain View, CA 94040 | 650-940-7000
815 Pollard Road | Los Gatos, CA 95032 | 408-378-6131
elcaminohealth.org

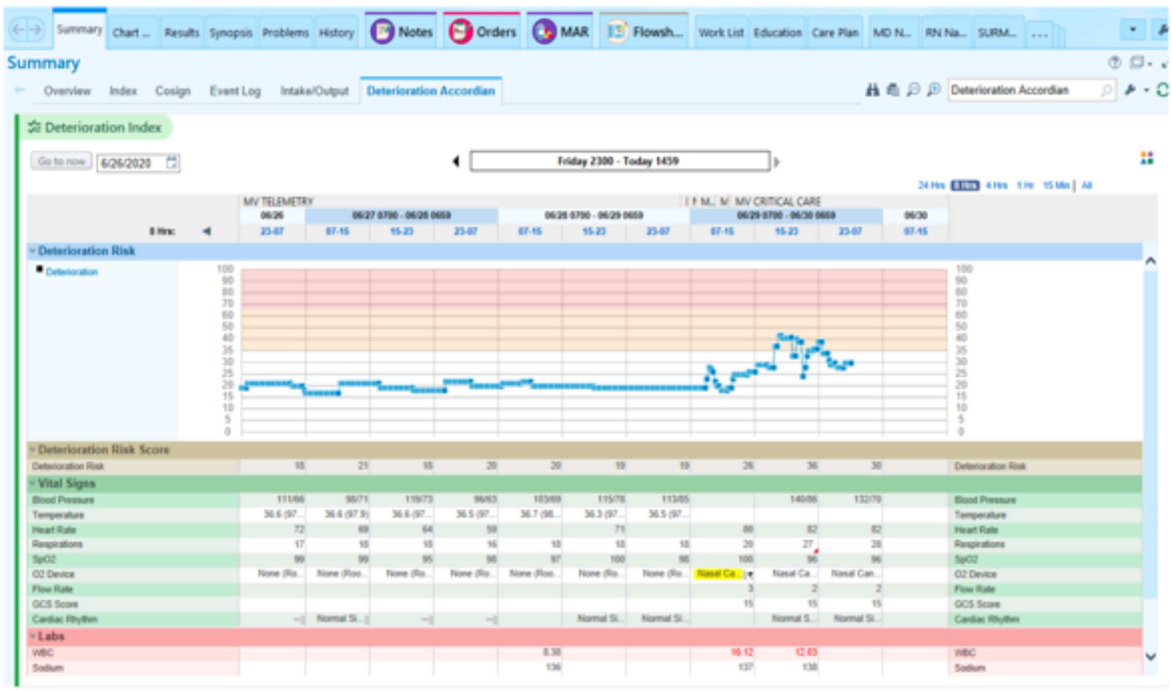
How to locate the Deterioration Index in EPIC

Where is the Deterioration Index in EPIC?
Go to 'Summary' Tab → the magnifying glass → select 'Deterioration Accordion'.

Add it as a favorite by clicking on the (wrench) icon and select 'Deterioration Accordion'.

What does the Deterioration Accordion look like? *See below*

What will trigger the DI-initiated RRT? At this time, if your patient exceeds 65 on the Deterioration Risk scale or has a 13 point increase, the artificial intelligence will activate an RRT.



Posted
July 8, 2020

Appendix P

Data Collection Tools

Figure 1. Pre-Intervention

Campus	Cardiac Arrest Outside ICU	AI On/Off	# of Rapid Responses
MV	02/06/19	Off	2
LG	03/01/19	Off	2
MV	03/26/19	Off	0
MV	04/01/19	Off	3
MV	04/04/19	Off	0
MV	04/04/19	Off	0
MV	05/12/19	Off	0
MV	05/20/19	Off	0
MV	06/06/19	Off	1
MV	06/10/19	Off	4
MV	07/01/19	Off	4
MV	07/07/19	Off	2
MV	07/20/19	Off	0

Figure 2. Post-Intervention

Campus	Cardiac Arrest Outside ICU	AI On/Off	# of Rapid Responses	# of DI Notifications
MV	05/03/20 06:39	On	1	6
MV	05/08/20 12:05	On	0	29
LG	05/14/20 09:30	On	1	16
MV	06/06/20 00:00	On	0	10
LG	06/11/20 03:00	On	2	10
MV	06/28/20 19:17	On	0	8
MV	06/29/20 06:46	On	0	10
MV	07/22/20 06:06	On	1	13
MV	07/24/20 18:15	On	2	12

Appendix Q

PDSA Worksheet

Project: Deterioration Index

Project Lead: Alicia Potolsky

Team Members: Cally Oxford; Andrew Baca; Jina Canson; Tom Tenino; Elaina Huong; Denise Robb; Justin Stuart; Laurie Santo; Jolie Fournet; Jim Canfield; Pamela Fiehmann

Aim: Implement Epic's Deterioration Index into hospital's EHR to supplement RRT activation process **Current Baseline:** Only Staff activate RRTs

Cycle #: 1 **Date Range:** February 4, 2020 to February 27, 2020

Describe your first (or next) test of change:	Evidence	Person(s) responsible	When to be done	Where to be done
1. Trail initial DI threshold of 60 to alert RRT RN via Vocera. 2. RRT RN proactively round on pts with DI scores greater than 60. Proactive rounding will include step of "mark as reviewed".	1. Based off July-Nov data provided by Epic and DI 2. Teams retrospective review of RRTs, codes in relation to DI scores.	RRT RNs	Feb 4 – 19	Both MV and LG campus.

Plan

List the tasks needed to set up this test of change	Person(s) responsible	When to be done	Where to be done
1. Determine thresholds and logic for alert. 2. Build and test alert 3. Finalize expectations for RRT RN 'proactive rounding & mark as reviewed', i.e. standard work 4. Communicate to Cycle 1 test of change to stakeholders	1. DI team 2. Cally 3. Justin, Connie & Alicia 4. DI Team	1. 12/6 2. 1/10 3. 1/17-24 4. 1/29-2/3	1. DI Mtng 2. iCare 3. On-line 4. Flex RN meeting

Predict what will happen when the test is carried out	Measure(s) to determine if prediction succeeds
1. RRT RNs will round on more pts 2. RRT RN intervention prior to primary RN calling RRT 3. Number for staff activated RRTs, Code Blues, and THLOC would be less.	1. Monitor workload changes during pilot via tracking sheet. 2. RRT RN to track if DI alert would have developed to RRT call via tracking sheet. 3. Track via pilot data tracking sheet. Cross referenced to CPR committee data.

Do

Describe what actually happened when you ran the test

Per 2/14 DI Workgroup meeting:

- "Day 4 with was better…felt like I knew the pts, then when new pts would trigger DI alert, would first review chart, then check with the RN"
- "Missed some DI alerts because did not hear the ping"
- "DI score could fluctuate in a couple of hours"
- "Sometimes I get a DI alert on a pt, but when I review the chart, there is no score over 60" - *iCare analyst hypothesizes this may be related to file time only occurs every 15 minutes, so if values that triggered DI over 60 corrected within the 15 minute file interval, the inaccurate DI score would not be filed. Need to confirm with Epic.*
- "Feel like the workload had increased tremendously because of the DI process, but also high census right now too"
- "Adding a trigger point when DI score jumps 15 points or more between to scores (even if under 60) may be helpful"
- "Could the Charge RNs be included in the DI alerts?"
- "Issue DNR pt on morphine drip, but no Goals of Care or comfort care orders"
- "Heavy emphasis on neuro. RNs documenting GCS incorrectly and setting it falsely high. RNs need re-education on when and how to assess GCS"
- "High number of DI alerts on PCU pts", "Is it possible to exclude PCU" – *should not exclude.*
- "Jump add would help, 15 points or higher between last two scores should trigger DI alert"
- "Exclude OR and possibly peri-op services"

Study

Describe the measured results and how they compared to the predictions
Summary of data 2/4 to 2/14 • Number of recorded RRTs in Epic = **11** (2/4=2, 2/7=3, 2/8=1, 2/9=1, 2/11=2, 2/13=2) • Number of RRT Critiques from MCCM = **10** (down 45% compared to 2019 2019 2/4-2/14=18 RRTs) • Number of DI Alerts = **152** ~15/day (sample breakdown: 2/14, total 13 DI Alerts, 7 PCU, 4 3C, 1 4B, 1 LGOR)s **# of RN activated RRs:** • Jan 4 to Jan 30 = 27 RRs, Average = (27/26 days) 1.03 / day • Feb 4 to Feb 27 = 16 RRs, Average = (16/27 days) 0.89 / day **# of DI-Alerts:** • Feb 4 to Feb 27 = 270, Average = (270/16) 11.73 / day **# of Code Blues outside ICU** • Jan 4 to Jan 30 = 1 (3B) [not counting 1 in CCL, peri-op area excluded] • Feb 4 to Feb 27 = 0

Act

Describe what modifications to the plan will be made for the next cycle from what you learned	Person(s) responsible	When to be done	Where to be done
• Added rule to exclude patient admitted to GIP (General IP Hospice) For next cycle plan to: • Add 15 point DI score trigger • Add colors indicating high/medium/low risk on patient list & accordion view • Change 'High" threshold to 62	Cally Oxford	Feb 5	Feb 5

Cycle #: 2 Date Range: April 20, 2020 to May 5, 2020

Describe your first (or next) test of change:	Evidence	Person(s) responsible	When to be done	Where to be done
1. Trail expanded DI alert, cycle 1 configuration plus 15 point jump to alert RRT RN via Vocera. 2. RRT RN proactively round on pts with DI scores greater than 62. Proactive rounding will include step of "mark as reviewed". 3. Add color indicators for high, medium, low DI scores on pt list and DI accordion views.	1. Based off July-Nov data provided by Epic and from cycle 1, test of change 2. RRT RNs to continue to incorporate review of 'known' pts (DI>62) into Standard Work.	RRT RNs	April 15 – May 5	Both MV and LG campus.

Plan

List the tasks needed to set up this test of change	Person(s) responsible	When to be done	Where to be done
1. Assess need for additional and logic or modifications of alert. 2. Rapid Response RNs to follow standard work for DI Alert 3. Educational flier sent to all RR RNs on 4/15 4. RR RNs to complete self-assessment of adherence to standard work at end of each shift. 5. Present Cycle 2 specs and process at Flex RN meeting	1. Cally 2. Alicia / Cathy 3. Connie 4. RR RNs 5. Alicia		

Do

Predict what will happen when the test is carried out	Measure(s) to determine if prediction succeeds
1. RRT RNs will round on more pts 2. RRT RN intervention prior to primary RN calling RRT 3. Number for staff activated RRTs, Code Blues, and THLOC would be less.	1. Monitor number of RRTs, and DI Alerts 2. Review self-assessments

Describe what actually happened when you ran the test
• On April 20 'false start' to cycle 2. Configuration issue causing DI Alert to send Vocera text message to RRT RN nearly every minute. Turned off until configuration issue fixed. Back on the following day 4/21. • Discovered alerts firing on discharged patients. May have been occurring during first cycle but due to high census not discovered. During this cycle, census low and rooms unoccupied longer than usual after patient discharges. • As of 4/29: 26 self-assessments competed. RR RNs using self-assessment as method to report issues with DI Alert vs reflection on adherence to standard work.

Study

Describe the measured results and how they compared to the predictions
# of RN activated RRs: • Apr 21 to May 5 = 13 RRs, Average = 0.81 / day **# of DI-Alerts:** • Apr 21 to May 5 = 97, Average = 6.46 / day **# of Code Blues outside ICU** • Apr 21 to May 5 = 1 on 3B 5/3 @6:39

Act

Describe what modifications to the plan will be made for the next cycle from what you learned	Person(s) responsible	When to be done	Where to be done
• Add rule to DI Alert to exclude discharged pts. • Add rule to DI Alert to exclude peri-op pts. • Change DI score jump rule for 15 to 10.	Cally & Andrew		

Cycle #: 3 Date Range: May 6, 2020 to May 15, 2020

Describe your first (or next) test of change:	Evidence	Person(s) responsible	When to be done	Where to be done
1. Add rule to DI Alert to exclude discharged pts. 2. Add rule to DI Alert to exclude peri-op pts. 3. Change DI score jump rule for 15 to 10.	1. Having DI Alerts on empty rooms, after investigation, pts had been in that room, were discharged and the following day follow up charting from CC causing DI to recalculate. 2. Having DI Alerts on peri-op pts. Not necessary. 3. RR RNs wanted to trial a more sensitive trigger for increases.	Cally & Andrew		

Plan

List the tasks needed to set up this test of change	Person(s) responsible	When to be done	Where to be done
1. Add rule to DI Alert to exclude discharged pts. 2. Add rule to DI Alert to exclude peri-op pts. 3. Change DI score jump rule for 15 to 10.	1. Cally	1.	1.

Do

Predict what will happen when the test is carried out	Measure(s) to determine if prediction succeeds
1. More appropriate pts will be identified.	1. If pts in need of RR RN intervention more often.

Describe what actually happened when you ran the test
• 10 point jump too sensitive. • Many patients I with DI score in low 60s no interventions needed, chronically high. Many already in PCU.

Study

Describe the measured results and how they compared to the predictions
# of RN activated RRs: • May 6 to May 15 = 8 RRs, Average = 0.89 / day **# of DI-Alerts:** • May 6 to May 15 = 195, Average 22 / day **# of Code Blues outside ICU** • May 6 to May 15 = 2 (3C on 5/8@12:05 & LG Rehab on 5/14@09:30)

Act

Describe what modifications to the plan will be made for the next cycle from what you learned	Person(s) responsible	When to be done	Where to be done
• Change DI Alert "High" threshold to 65 • Change DI Alert jump trigger to 13	Cally O.	May 15	Epic

Cycle #: 4 Date Range: May 15, 2020 to May 19, 2020

Describe your first (or next) test of change:	Evidence	Person(s) responsible	When to be done	Where to be done
1. Change DI Alert "High" threshold to 65 2. Change DI Alert jump trigger to 13		Cally O.	May 15	Epic

Plan

List the tasks needed to set up this test of change	Person(s) responsible	When to be done	Where to be done
1. Change DI Alert "High" threshold to 65 2. Change DI Alert jump trigger to 13	1. Cally O.	1. May 15 2. May 15	Epic

Do

Predict what will happen when the test is carried out	Measure(s) to determine if prediction succeeds
1. DI Alerts will decrease.	1. DI alerts decrease and those that do fire meaningful action can be taken.

Describe what actually happened when you ran the test
• Noticeable number of PCU pts DNR awaiting goals of care decisions, palliative care consults.

Study

Describe the measured results and how they compared to the predictions
# of RN activated RRs: • May 15 to May 19 = 3 RRs, Average = 1 / day **# of DI-Alerts:** • May 15 to May 19 = 79, Average 15.8 / day **# of Code Blues outside ICU** May 15 to May 19 = 0

Act

Describe what modifications to the plan will be made for the next cycle from what you learned	Person(s) responsible	When to be done	Where to be done
• Add 24 hours suppress after 'mark as reviewed' for pts with active DNR order.	Cally O.	May 20	Epic

Cycle #: **4.5** **Date Range:** **May 20, 2020 to May 25, 2020**

Describe your first (or next) test of change:	Evidence	Person(s) responsible	When to be done	Where to be done
• Add 24 hours suppress after 'mark as reviewed' for pts with active DNR order.	Many DI Alerts for DNR pts without comfort care orders or goals of care addressed.	Cally O.	May 20	Epic

Plan

List the tasks needed to set up this test of change	Person(s) responsible	When to be done	Where to be done
Add 24 hours suppress after 'mark as reviewed' for pts with active DNR order.	Cally O.	May 20	Epic

Do

Predict what will happen when the test is carried out	Measure(s) to determine if prediction succeeds
2. DI Alerts will decrease for patients with continually high DI scores that are waiting for goals of care planning.	2. DI alerts decrease and those that do fire meaningful action can be taken.

Describe what actually happened when you ran the test
• Noticeable number of PCU pts DNR awaiting goals of care decisions, palliative care consults.

Study

Describe the measured results and how they compared to the predictions
# of RN activated RRs: • May 20 to May 25 = 4 RRs, Average = 1 / day **# of DI-Alerts:** • May 20 to May 25 = 75, Average 12.5 / days **# of Code Blues outside ICU** May 20 to May 25 = 0

Act

Describe what modifications to the plan will be made for the next cycle from what you learned	Person(s) responsible	When to be done	Where to be done
• Add charge RNs to receive DI Alert Vocera message. • Education to charge RNs on what to do when they receive DI Alert Vocera text message	Cally O. Alicia P. & Connie M.	May 26	Epic Huddles, e-mail, other announcements

Cycle #: 5 **Date Range: May 26, 2020 to July 13th**

Describe your first (or next) test of change:	Evidence	Person(s) responsible	When to be done	Where to be done
• Add charge RNs to receive DI Alert Vocera message. • Education to charge RNs on what to do when they receive DI Alert Vocera text message	Current staff driven RRT notifications include all charge RNs so they can work with primary RN on assessing patient situation prior to RRT RN arrival	Cally Alicia & Connie	May 26 May 18-26	Epic e-mail, huddles, announcements,& rounding

Plan

List the tasks needed to set up this test of change	Person(s) responsible	When to be done	Where to be done
1. Add charge RNs to receive DI Alert Vocera message. 2. Education to charge RNs on what to do when they receive DI Alert Vocera text message	Cally Alicia & Connie	May 26 May 18-26	Epic e-mail, huddles, announcements,& rounding

Do

Predict what will happen when the test is carried out	Measure(s) to determine if prediction succeeds
1. Decrease RRT RN time on false alarms 2. Engage unit staff	1. Monitor number for DI notifications and feedback from RRT RNs 2. Feedback from rounds

Describe what actually happened when you ran the test
• 5/29 – ED admissions firing alert, no rule to suppress on admission. • 6/5 – Mixed results on charge RNs adoption and understanding to DI Alert workflows. Ongoing concerns with RN accuracy in documenting GCS. • PCU remains the unit with the highest number of DI Alerts

Study

Describe the measured results and how they compared to the predictions
# of RN activated RRs: • May 26 to July 12 = 32 RRs, Average = 0.67 / day **# of DI-Alerts:** • May 26 to July 12 = 593, Average 12.35 / day **# of Code Blues outside ICU** May 26 to present (end July 12) = 4 (3B on 6/6@00:00, LG MS on 6/11@03:00, PCU on 6/28@19:17, PCU on 6/29@06:46)

Act

Describe what modifications to the plan will be made for the next cycle from what you learned	Person(s) responsible	When to be done	Where to be done
• Meet with PCU management to discuss possibility of PCU Charge RNs following same standard work as RRT RNs to 'mark as reviewed" those known chronically high patients. • Checking with other Epic sites on DI triggers and unit inclusions • End standard work Self-Assessment • Target DI-RRT go live July 13 • Meet with Education Team to plan roll out communication • Create flowchart • Education campaign to start July 6	• Alicia • Alicia, Beth & Connie	June 7-18 June 15-July 6	

On Monday July 13, 2020 will end PDSA – Officially change to "DI-RRTs"

Appendix R

Outcome Measures

Figure 1. Cardiac Arrest Pre- and Post-Intervention

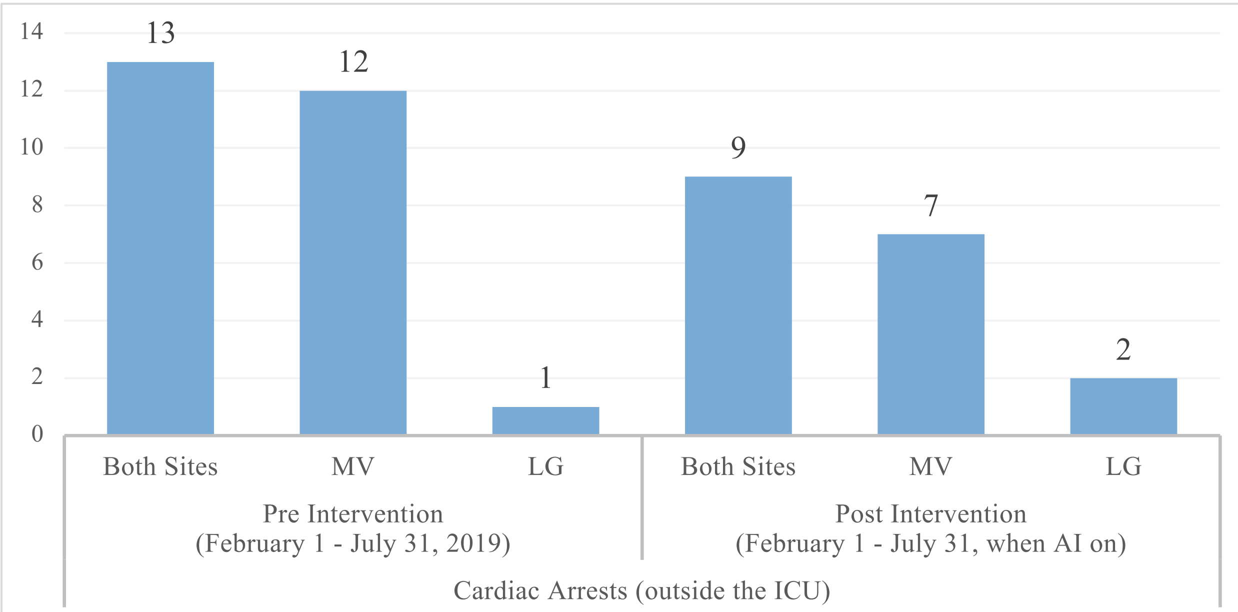
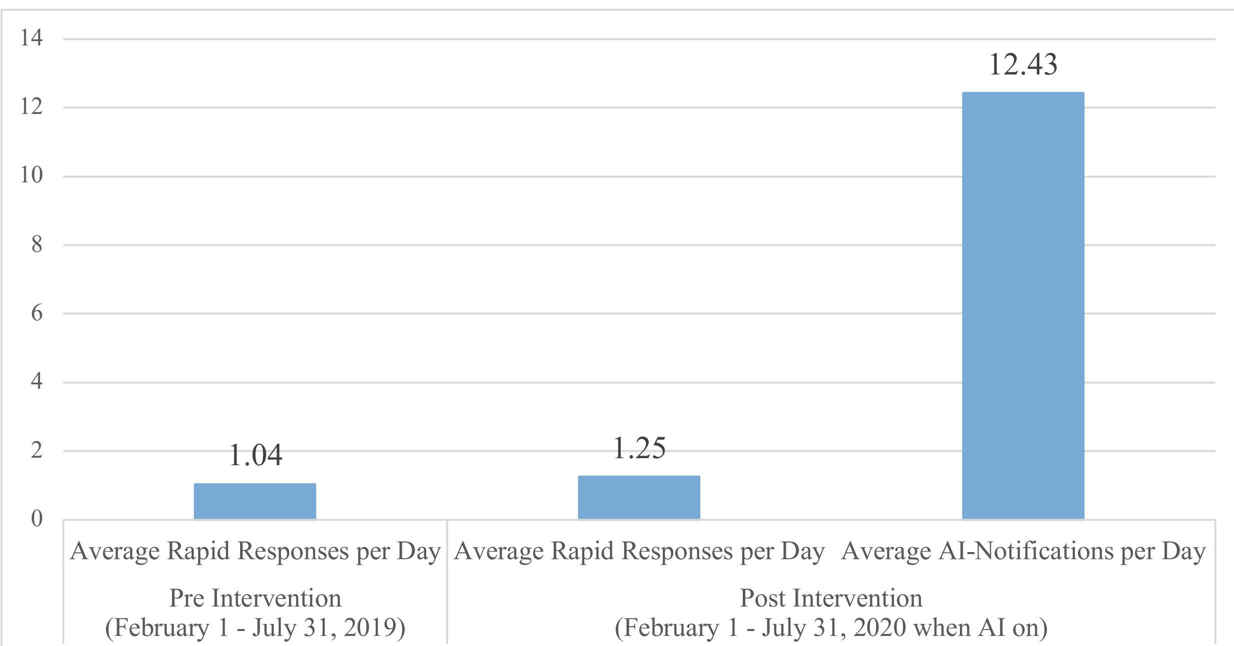
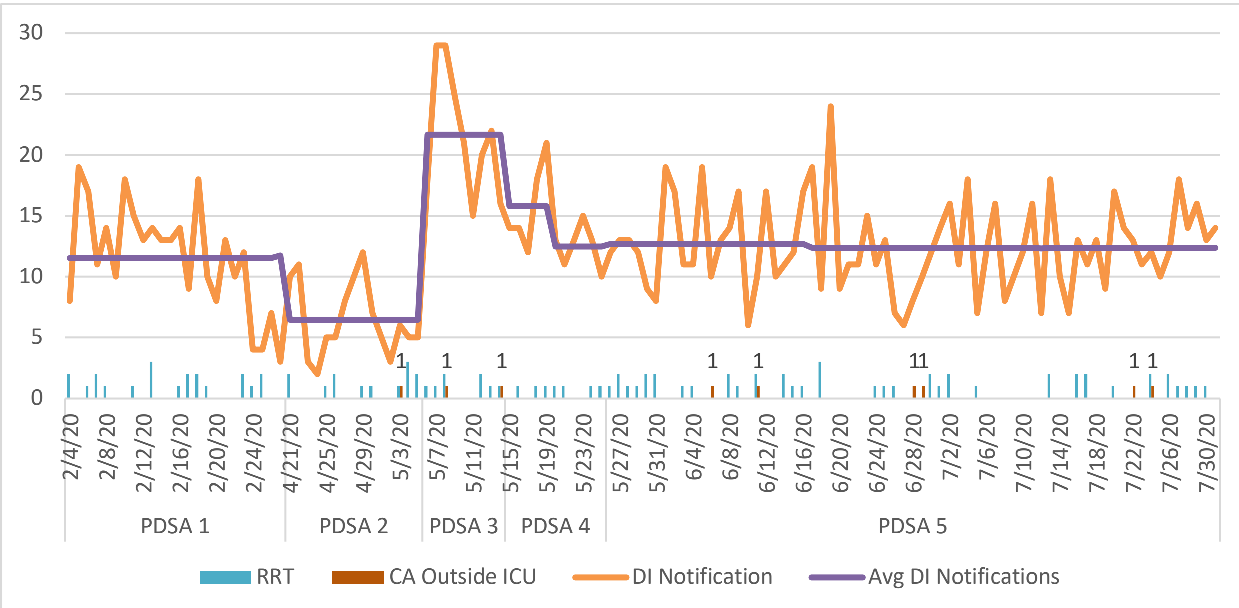


Figure 2. Rapid Responses Pre- and Post-Intervention



Appendix S

Metrics Over Time



Appendix T

Standard Work Self-Assessment

DI Alert - Standard Work Self Assessment

Thursday, May 28, 2020

Powered by

1

89

Total Responses

Date Created: Monday, April 13, 2020

Complete Responses: 89

Powered by SurveyMonkey

Q1: I followed the standard work process for Change of Shift:

Answered: 89 Skipped: 0

	YES	NO	TOTAL
Reviewed DI Patient List with off-going RRT RN	96.63% 86	3.37% 3	89
Sorted patient list by highest DI score to lowest	88.76% 79	11.24% 10	89
Reviewed each patient with score of 62 or greater	78.65% 70	21.35% 19	89

Powered by SurveyMonkey

3

Q2: I followed the standard work process for DI Alert During Shift:

Answered: 89 Skipped: 0

	YES	NO	N/A (NO DI ALERTS DURING SHIFT)	TOTAL
Reviewed the patient's score contributors via the DI patient list	85.39% 76	1.12% 1	13.48% 12	89
Reviews patient's DI trend graph via Deterioration Accordion view	85.39% 76	1.12% 1	13.48% 12	89
Called the unit to speak with primary RN	74.16% 66	8.99% 8	16.85% 15	89
If indicated, called RRT	11.24% 10	21.35% 19	67.42% 60	89
Documented in patient record any interventions	34.48% 30	16.09% 14	49.43% 43	87
Updated the DI Patient List, with "Mark as Reviewed" with a brief standard note.	76.14% 67	4.55% 4	19.32% 17	88
Completed a RRT Critique	2.27% 2	18.18% 16	79.55% 70	88

Powered by SurveyMonkey

Q3: I followed the standard work process for Rapid Response Alert:

Answered: 89 Skipped: 0

	YES	NO	N/A (NO RRTS DURING SHIFT)	TOTAL
Responded to RRT	10.11% 9	2.25% 2	87.64% 78	89
Documented in the Rapid Response Narrator	10.98% 9	1.22% 1	87.80% 72	82
Completed RRT Critique	9.64% 8	2.41% 2	87.95% 73	83
Updated the DI Patient List, with "Mark as Reviewed" with a brief standard note.	25.61% 21	6.10% 5	68.29% 56	82

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7

Q4: My response time was:

Answered: 72 Skipped: 17

	DI ALERT VOCERA TEXT	STAFF INITIATED RAPID RESPONSE	TOTAL RESPONDENTS
0 to 5 minutes	90.32% 28	12.90% 4	31
5 to 15 minutes	100.00% 33	0.00% 0	33
15 minutes to 30 minutes	92.86% 13	7.14% 1	14
More than 30 minutes	100.00% 14	0.00% 0	14
Unable to respond	83.33% 5	16.67% 1	6

Powered by SurveyMonkey

Appendix U

Signed Statement of Non-Research Determination Form

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DNP Statement of Non-Research Determination Form

Student Name: **Alicia Potolsky**

Title of Project: Artificial Intelligence (AI) Activated Rapid Response Teams

Brief Description of Project:

A) Aim Statement: The project aim is to reduce in-hospital cardiac arrests through the implementation of artificial intelligence (AI) into the existing electronic health record (EHR) in order to recognize and notify the rapid response team of patient deterioration sooner.

B) Description of Intervention: The project is to implement Epic's machine learning Deterioration Index module into the target organization's electronic health record (EHR). Using the plan-do-study-act (PDSA) quality improvement process, the project will integrate automated alerting into the established rapid response system to increase earlier recognition, notification, and intervention of patient deterioration and therefore reduce in-hospital cardiac arrests.

C) How will this intervention change practice? This project will change practice by adding automated notification of the rapid response team (RRT) into the organization's existing activation process. Based on other organization's experience with implementing this software into the rapid response system, this intervention is expected to increase the number of rapid responses, decrease the number of in-hospital cardiac arrests, and possibly decrease the number of transfers to a higher level of care.

D) Outcome measurements: The primary measure will be the number of in-hospital cardiac arrests. Information will also be collected pre and post-implementation on the number of rapid responses, nurse-activated rapid responses, AI-activated rapid responses, patients transferred to a higher level of care, the time of day and location of the events; and the impact on the rapid response team.

To qualify as an Evidence-based Change in Practice Project, rather than a Research Project, the criteria outlined in federal guidelines will be used: (http://answers.hhs.gov/ohrp/categories/1569)

☑ This project meets the guidelines for an Evidence-based Change in Practice Project as outlined in the Project Checklist (attached). Student may proceed with implementation.

☐ This project involves research with human subjects and must be submitted for IRB approval before project activity can commence.

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EVIDENCE-BASED CHANGE OF PRACTICE PROJECT CHECKLIST *

Instructions: Answer YES or NO to each of the following statements:

Project Title:	**YES**	**NO**
The aim of the project is to improve the process or delivery of care with established/ accepted standards, or to implement evidence-based change. There is no intention of using the data for research purposes.	☑	
The specific aim is to improve performance on a specific service or program and **is a part of usual care**. ALL participants will receive standard of care.	☑	
The project is **NOT** designed to follow a research design, e.g., hypothesis testing or group comparison, randomization, control groups, prospective comparison groups, cross-sectional, case control). The project does **NOT** follow a protocol that overrides clinical decision-making.	☑	
The project involves implementation of established and tested quality standards and/or systematic monitoring, assessment or evaluation of the organization to ensure that existing quality standards are being met. The project does **NOT** develop paradigms or untested methods or new untested standards.	☑	
The project involves implementation of care practices and interventions that are consensus-based or evidence-based. The project does **NOT** seek to test an intervention that is beyond current science and experience.	☑	
The project is conducted by staff where the project will take place and involves staff who are working at an agency that has an agreement with USF SONHP.	☑	
The project has **NO** funding from federal agencies or research-focused organizations and is not receiving funding for implementation research.	☑	
The agency or clinical practice unit agrees that this is a project that will be implemented to improve the process or delivery of care, i.e., **not** a personal research project that is dependent upon the voluntary participation of colleagues, students and/ or patients.	☑	
If there is an intent to, or possibility of publishing your work, you and supervising faculty and the agency oversight committee are comfortable with the following statement in your methods section: *"This project was undertaken as an Evidence-based change of practice project at X hospital or agency and as such was not formally supervised by the Institutional Review Board."*	☑	

ANSWER KEY: If the answer to **ALL** of these items is yes, the project can be considered an Evidence-based activity that does NOT meet the definition of research. **IRB review is not required. Keep a copy of this checklist in your files.** If the answer to ANY of these questions is **NO**, you must submit for IRB approval.

*Adapted with permission of Elizabeth L. Hohmann, MD, Director and Chair, Partners Human Research Committee, Partners Health System, Boston, MA.

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STUDENT NAME (Please print):
Alicia Potolsky

Signature of Student: Alicia Potolsky **DATE 8/3/2019**

SUPERVISING FACULTY MEMBER (CHAIR) NAME (Please print):
Priscilla Javed

Signature of Supervising Faculty Member (Chair): Priscilla Javed **DATE** 8/24/19