Improving patient care through analytics

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***Abstract*—Use of advanced electronic health record (EHR) systems has grown rapidly in the United States. This has created an abundance of data previously unavailable for analysis. Many health organizations now have reporting systems for operational key performance indicators (KPIs) and regulatory metrics and data warehouse systems for analytics. However, using this increasing information as meaningful knowledge to increase quality of care remains a challenge. This paper provides our experience utilizing an enterprise data warehouse and business intelligence tools to improve clinical outcomes for patients.**

Healthcare Informatics; Data Warehousing; Business Intelligence; Industry Experience

I. Introduction

Loma Linda University Health System maintains all medical records using their EHR system. We have implemented the EHR's data warehouse solution and extended it to become a true enterprise data warehouse including detailed clinical and operational information for each hospital visit.

We created KPIs and business intelligence tools to analyze clinical outcomes. We defined clinical outcomes as length of stay, readmissions, and mortality. The goal is to reduce each of these measures. We analyzed these outcomes by diagnosis and diagnosis-related group (DRG). We compared the results with benchmarks of averages from other hospitals and targets established by the Center for Medicaid and Medicare Services (CMS). We used this analysis to identify clinical areas with the greatest opportunity for improvement. Fig. 1 shows one of our analytic dashboards for identifying areas to target.

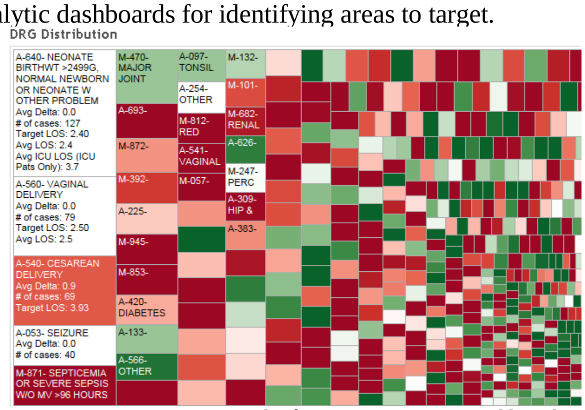


Figure 1. Length of Stay Opportunities Dashboard

We then developed work groups where quality clinicians worked with the business intelligence team to develop analytics for each targeted clinical program. Clinical programs identify a specific patient population based on acute or chronic diagnoses, physical hospital location, and performed hospital procedures. Each clinical program has applicable clinical KPI's to track. The clinical programs developed so far include congestive heart failure (CHF), sepsis, exacerbated chronic obstructive pulmonary disease (COPD), pediatric pneumonia, pediatric bronchiolitis, and pediatric asthma. These same work groups and clinicians were involved from beginning to end of the project to perform user acceptance testing and to enable rollout to the hospital users.

Additionally, we identified two key clinical events that affect clinical outcomes: hospital-acquired infections and blood transfusions [1]. To address hospital-acquired infections, we created two analytic programs. We created an analytical program centered around the use of ventilators, one of the leading causes of hospital-acquired infections. The second program was the Prevent Pain and Organisms from sKin and catheter Entry and Radiology (POKE-R) program. To address blood transfusions, we analyze the clinical events preceding the order to determine the necessity of the transfusion.

In the remaining sections of this paper, we will identify the data points for analysis and the technical challenges and solutions. We will then describe the solution provided and the results so far.

II. Clincal programs

A. Sepsis

Septic shock occurs when organ injury from infection leads to dangerously low blood pressure and abnormalities in cellular metabolism. Severe sepsis and septic shock have one of the highest rates of hospital mortality, with estimates ranging from 25 to over 50% [2] [3]. The identified key metrics for sepsis are antibiotic administration, lactate collection, blood culture collection, central venous pressure (CVP), and fluid resuscitation. Sepsis treatment is extremely time-sensitive so the most important metric is the number of minutes from arrival and/or instances of an EHR decision support alert to these clinical events. Additionally, fluid resuscitation requires a specific amount of fluid administration per kg of the patient's weight.

B. *Congestive Heart Failure*

Congestive heart failure occurs when the heart function is unable to provide sufficient blood flow to the body. CHF hospital visits incur 4.4% mortality and 60% readmission rate [5]. 5.1 million people in the United States have heart failure and about half die within five years of diagnosis [4].

The identified key metrics for CHF are intravenous diuretic administration, brain natriuretic peptide (BNP) test, daily weight administration, and follow-up visits after discharge. CHF is time sensitive so a key metric is the time from arrival to administration of the diuretic.

C. *Pediatric Asthma and Bronchiolitis*

Asthma is a respiratory condition marked by bronchial spasms. 8.6% of children in the United States under 18 currently have asthma and there are 439.000 inpatient hospital visits a year [7]. In a NIH study, 15% of pediatric asthma patients were readmitted [6]. Bronchiolitis is inflammation of the bronchioles, the smallest air passages of the lungs. It usually occurs in children less than two years of age with the majority being aged between three and six months. We are grouping them together here because they have the same key clinical metrics.

The identified key metrics for pediatric asthma and bronchiolitis are bronchodilator and steroid administration. Asthma is time sensitive so a key metric is the arrival time to the administration time.

D. *Pediatric Pneumonia*

15% of all child deaths are caused by pneumonia, over 900,000 annually world-wide [8]. Pneumonia is an infection of the lungs so the key clinical metric is antibiotic administration. This includes both the time from arrival to administration and the duration of the administration.

E. *Exacerbated COPD*

COPD is a chronic lung disease including emphysema and chronic bronchitis. Exacerbated COPD is an acute instance of worsening COPD that requires medical attention in the inpatient or outpatient setting. In the United States, occurrences of exacerbated COPD are expected to rise significantly over the next 20 years [9]. In 1990, 2.2 million people died from COPD exacerbation and that number is expected to increase to 3.5 million by 2020 [9].

The following key data points were identified for the exacerbated COPD clinical protocol: ventilator usage, administration of steroids, antibiotics, anticholinergics, beta agonists, methylxanthines and/or phospodiesterase-4 inhibitors, lab tests including chemistry, arterial and venous blood gasses, and glucose.

F. *Blood Utilization*

For blood utilization analysis, we limited the scope to red blood cells. Blood transfusions negatively affect the patient's immune system and increase the risk of acquiring an infection [1].

We evaluate each blood transfusion as clinically appropriate or not based on categories. The key metrics to categorize clinical necessity are hemoglobin, systolic blood pressure, blood loss, lactate, base deficit, venous oxygen saturation, and the presence of acute myocardial infarction.

G. *Ventilator*

Prolonged use of ventilator assisted breathing drastically increases infection risk, particularly pneumonia. "Pneumonia is the second most common nosocomial infection in critically ill patients, affecting 27% of all critically ill patients. Eighty-six percent of nosocomial pneumonias are associated with mechanical ventilation and are termed ventilator-associated pneumonia (VAP)"[10].

Our key data points for ventilation are the number of hours on the ventilator, and the number of ventilator placements.

H. *POKE-R*

Every time a line, drain, tube or airway (LDA) is placed in a patient, every time blood is drawn from a patient, every time medication is administered to a patient, there is increased risk for hospital-acquired infection, increased pain to the patient, and increased opportunity for blood loss[11]. This can reduce both clinical outcomes and patient experience. The problem is amplified in neonatal and pediatric patients where it is more challenging to place a line and where even a small amount of blood loss can cause complications [12][13].

For this project, we identify which clinical events are POKE-R events. We then monitor patients for the count of POKE-R events and we analyze upcoming scheduled events. The goal is to allow the clinician to reduce the number of POKE-R invasions performed.

III. Implementation and Challenges

We have built an enterprise data warehouse using software provided by the EHR combined with custom extensions developed at Loma Linda. Our enterprise data warehouse utilizes the traditional Kimball dimensional modeling approach with star schemata[17]. It was necessary to use several known strategies including late-arriving dimensions (to allow daily extract, transform and load (ETL) to execute even if some information was not available) and durable surrogate keys (to allow aggregation across slowly changing dimensions and multiple source data sets).

This data warehouse allows us to get to a substantial amount of detailed information which is conformed across the hospital encounter. This includes details on every medication administration, clinical documentation and lab result. We have extended the data warehouse to include progress notes, best practice alerts, line, drains and airways placements, DRGs and other clinical details. Also, it was necessary for many of our metrics to know the unit or level of care the patient was currently in. The EHR maintains a table of every patient update such as admissions, transfers, discharges and changes in level of care, bed, patient class or service. We built 4 tables on top of this. Three are summarized small accumulated snapshots for level of care, service and bed, showing when the patient entered and left the bed, level of care or service. The fourth table is a census snapshot by date showing which patient is in each bed in the hospital.

Next, we built custom reporting tables or views for each of our programs. This enabled simpler reporting and better performance. We faced several challenges in this.

For blood utilization we needed to determine the exact number of units administered. Several of our early attempts, including looking at clinical documentation and order status, failed to give us an accurate account due to workflow and documentation inconsistencies. Each unit of blood requires a label. We were finally able to get accurate information by directly mining the label printing actions. Discarded units were being properly documented and were rare so we were able to take that into account. Another challenge with blood utilization is that we need to not just look at lab results but look at the delta in lab results over specific periods of time. We built an auxiliary table which monitored delta ranges for lab results. This allowed this information to be updated with standard incremental load and easily accessed.

For POKE-R, there were also many challenges. We had to add two extractions specifically for this project. We added an extension and modified EHR workflow specifically for LDAs to know how many attempts the LDA placement took. Furthermore, physician-performed LDAs such as central lines were documented in a different manner so we created a special extract to get the placement times and attempts. Finally, it was not enough to know when a specimen was taken. We needed to know which procedure orders shared blood draws and which required separate blood draws. If 5 lab draws show the same collection time, it is important to know whether they were separately drawn, or all of the tests used the same blood collection.

With these extensions, all of the data needed to mine the POKE-R information was available in the data warehouse. However, before we could search for the POKE-R events, we had to configure which events were defined as POKEs. We did not want to hard-code this information and we did not want the information determined or maintained by IT personnel as it is clinical in nature. Therefore, we established an interface to configure POKE-R.

We needed to define every event which was a POKE-R event and whether it was painful. This needs to be configured using attributes of the data elements. The following attributes were identified by the clinician as identifying POKEs:

1. Medication Administration: Route and Administration Event
2. Lab Test: Specimen Type and Specimen Source
3. Procedure Order: Type and Code

Additionally, the presence of a line or drain prior to the event can impact whether the event is a POKE and whether it is painful. For example, blood tests and medication administrations are considered non-painful if they use an existing line. A urine sample is not a POKE at all unless there is a catheter used to obtain the specimen.

We created a simple secure interface for the Patient Safety and Reliability leadership to provide and administer this clinical information. This interface contains the data points listed above prepopulated from the actual clinical data warehouse. The user can then choose which values for each data point indicate a POKE and can combine data points.

Another thing that was very important was to determine the scheduled POKE-R events. Our goal was to show the clinician the upcoming POKE-R schedule so that treatment could be altered to reduce the POKEs. To do this we brought in every scheduled medication administration, procedure, surgery, image or lab test.

IV. Distribution

The goal of our project is to utilize analytics to actually affect patient quality of care and clinical outcomes. To do this, we wanted to enable the business and clinicians to access appropriate information at appropriate times. This includes: operational reports for use during daily rounds, short-term retrospective reports and dashboards to learn opportunities for continuous improvement, long-term retrospective reports and dashboards to understand which programs are working and to establish or refine clinical programs, regulatory reports to calculate quality metrics established by the payors, government and credentialing agencies, and self-reporting systems to allow clinicians and quality experts to develop new reports on their own.

We held four guiding principles which guided our implementation. First, all information should be available for self-reporting. Second, the enterprise data warehouse should enable a single version of the truth and similar but distinct information should be clearly described in clinical terms. Third, to enable trust in the data, lineage should be available for each data point. Fourth, to allow for care improvement all data should be able to be drilled to the detailed data points underneath the KPIs. This specifically means we should be able to determine every hospital or visit encounter impacting a KPI.

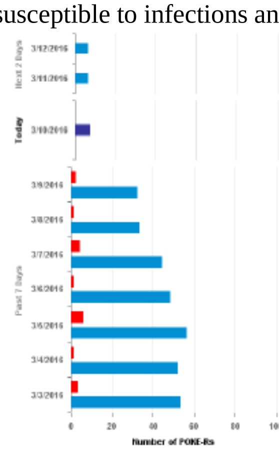
To enable this, we created a metadata layer which defined the data model and the business terms. We used SAP Business Objects [18] to create this model. The development of this model enabled ad-hoc reports to be created by end users through SAP Web Intelligence [18]. There were some challenges we had to overcome in the development of our metadata layer. Our source reporting tables and facts were generally at the lowest level of grain so any aggregations had to be defined in the metadata layer. However, many of the time-related metrics in healthcare utilize median rather than mean, and median is not a standard database SQL function, so we pre-calculated medians where appropriate in special median tables. Secondly, we encountered many data quality issues related to incorrect documentation in the source system. We did not cleanse the data coming into the data warehouse. However, it was necessary to cleanse the data for accurate reporting. For example, if a row shows a hospital arrival time that is later than the hospital discharge time, the actual length of stay will be negative. We cannot allow a negative length of stay to propagate inaccuracies in our average length of stay. So, we had to add many filters across the metadata layer to exclude errant values prior to performing measure calculation.

A. *Operational Reports*

To enable operational reporting, we chose specific areas to roll-out our solutions and developed simple and easily understood methods to get the information to the correct personnel. Specifically, for POKE-R we chose to begin the program in the pediatric intensive care unit (PICU). Pediatric patients are the most susceptible to trauma, infections and anemia from POKE-R events. Because we had included scheduled future events, clinicians had an opportunity to meaningfully impact patient care using the analytics while the patient was still in the hospital.

Our report was scheduled to be automatically printed in the PICU at 6am every morning so clinicians could bring the details with them on their daily rounds prior to most POKEs being performed for the day. A resident fellow and a clinical nurse specialist were assigned specifically to manage the implementation of the program and received the daily detailed report. This allowed them to examine the most critical patients and suggest opportunities for POKE-R reduction. Fig. 2 shows an example of the POKE-R report. At Loma Linda, the PICU uses structured interdisciplinary bedside rounds (SIBR)[14]. Under the SIBR methodology, all members of a patient's care team visit and communicate with the patient as a unit. Because the SIBR methodology includes careful review of lab work, it provides a perfect opportunity to address potential POKEs. Loma Linda has adjusted the SIBR methodology to include POKE-R. The methodology includes minimizing lab orders by performing a risk vs. benefit analysis for each test.

Additionally, three sets of patients were targeted as providing significant opportunity and actively managed. These were patients with traumatic brain injury (TBI), patients with asthma and patients with external ventricular drain (EVD) placements. These patients are especially susceptible to infections and complications [15] [16].



Three Day Summary - Meds Only

		POKE-R Counts		
POKE-R Source	Action Type	Yesterday	Today	Tomorrow
Medication Administration	Intravenous	28	7	6
	Totals	28	7	6

Three Day Summary - Non-Med POKE-R Types

		POKE-R Counts		
POKE-R Source	Action Type	Yesterday	Today	Tomorrow
Lab Draw	Blood	1	0	0
Lab Draw	Blood - Arterial	2	0	0
Lab Draw	Blood, Venous	1	0	0
LDA Placement	Urethral Catheter	1	0	0
Radiology Procedures	IMG9101	1	0	0
	Totals	6	0	0

Action Type	POKE-R Source	Provider	POKE-R Details	Sched. Time*	Future POKE-R Qty.*
Intravenous	Medication Admin.	AMIN, NOMISHA NAVINKUMAR	METRONIDAZOLE 500 MG/ 100 ML-SODIUM CHLORIDE (ISO) INTRAVENOUS PIGGYBACK	03:00	1
Intravenous	Medication Admin.	SYNNOTT, MEGANN LEIGH	LINEZOLID 600 MG/300 ML INTRAVENOUS SOLUTION	04:00	1
Intravenous	Medication Admin.	SIMPSON, JESSICA HELEN	LINEZOLID 600 MG/300 ML INTRAVENOUS SOLUTION	05:00	1
Intravenous	Medication Admin.	AMIN, NOMISHA NAVINKUMAR	METRONIDAZOLE 500 MG/ 100 ML-SODIUM CHLORIDE (ISO) INTRAVENOUS PIGGYBACK	09:00	1

Figure 2. POKE-R Abridged Daily Report

Furthermore, asthma patients often experience an excessive number of lab tests in order to monitor the effects of medication on patient potassium levels [16]. Traumatic brain injury patients often experience sodium instability which requires monitoring[15]. Therefore, these patients are likely to have a substantial number of POKE-R events and are particularly vulnerable to harm from these events. We were also able to use these same analytics to encourage utilization of simple and cost-effective potassium and sodium serum tests for these patients, rather than more expensive complete basic metabolic panels.

B. *Short-term Lessons Learned Analytics*

To enable our short-term lessons learned analytics we created custom Tableau [19] dashboards for each clinical program. We included the data points specific to the clinical programs but we also included our clinical outcomes including length of stay, mortality, readmission and critical care length of stay in each dashboard. These dashboards were delivered with a common look and feel, a common set of drop-down filters at the top (date range, facility, admitting unit, discharging unit, admitting provider, discharging provider, admitting service, discharging service, DRG, disposition, and patient class) and an online instructional document was provided. The drop-down filters allow clinical leadership and individual providers to drill down to the encounters which they have an opportunity to improve. Additionally, we added dashboards to allow us to look at encounters with specific issues such as excessive length of stay or failure to perform an expected lab test. Weekly meetings were scheduled with appropriate clinicians (examples: intensivist group, pulmonary group, cardiology group, hospitalist group and pediatrics group) to review recent outcomes in detail and discuss with colleagues. This generally was still retrospective and did not alter patient care during an active encounter. However, the opportunity for examining cases and outcomes regularly with colleagues allows for continuous process and personal improvement. Fig. 3 shows examples of our short term analytics dashboards.

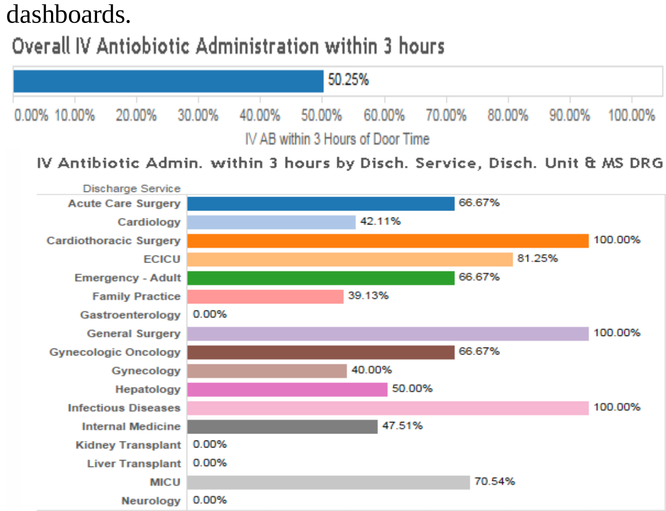


Figure 3. Example of short-term lessons learned dashboard

C. *Long-term Retrospective Dashboards*

The dashboards in the preceding section begin at the organizational level and use filters to drill down to lower grains, therefore the same dashboards can be used to evaluate organizational performance and search for improvement opportunities.

Additionally, we have dashboards that are not specific to any clinical program. These include length of stay, interdisciplinary rounds, discharge planning and more. In fact, these are the dashboards that we used to originally choose the clinical programs described here.

All of the dashboards described thus far evaluate clinical performance during specific date ranges. To truly evaluate the effectiveness of our clinical programs and performance improvement initiatives, we must trend each measure over time. This allows the clinicians and business leadership to see which programs are working, which are not, and alter the program details accordingly. Therefore, we have created dashboards which trend each metric over time. The user can adjust the time frames to look by year, quarter, month or even week. Fig. 4 shows an example of a trend-line dashboard.

D. *Quality Metrics*

Our data warehouse is not currently used for public reporting or reporting to credentialing oversight groups. It is used for some reporting to payers for specific benefit plans.

Nonetheless, the organization is required to report a vast number of quality metrics and is judged on these metrics. Metric compliance and performance can vastly effect reimbursement. Traditionally such reporting is done an annual basis. If the data is only looked at annually, there is little opportunity for near term improvement. Therefore, we are utilizing our data warehouse and analytics system to look at our metric performance at more regular time intervals.

To enable this, we develop metrics related to each core measure or quality metric. This includes metrics for many of the clinical programs listed here, and metrics that are outside the scope of this paper, such as population health. For acute encounter-based metrics, we recalculate the metrics as each hospital visit is loaded into the system. For patient-based population health metrics, we calculate the metrics in monthly snapshots and look over measurement periods. This allows us to combine programs for chronic diseases such as COPD, asthma and coronary artery disease with the acute hospital clinical programs we have described.

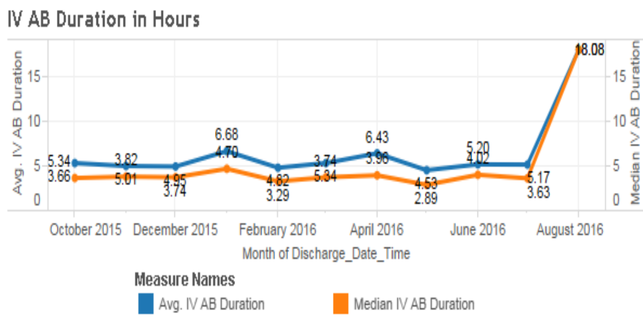


Figure 4. Example of a long-term trending dashboard element

We then provide two different levels of reporting. First we provide detailed reports which show complete lists of encounters and patients and highlight instances of non-compliances.

Second, we provide dashboards which show how a provider, location or facility are performing over time for specific metrics. We have loaded into our system benchmark information from CMS and other locations to allow us to show results compared to targets. We have connected these visualizations so the user can drill from the overall metric performance to the specific encounters and patients. This enables care gaps to be addressed and increases data understanding and trust with the clinicians.

E. *Self-Reporting*

As we have already described, our metadata layer and toolset enables self-reporting. Each data point is clearly described and the relationships (which create the database SQL joins) and groupings are defined in the metadata layer so the user only needs to choose the appropriate data objects and filters they would like using the interactive SAP tools.

The largest challenge to self-reporting is user adoption. We have provided classroom instruction but we do not believe this is sufficient. The only path to success we have seen materialize is personalized training and mentoring. For this to be scalable across a large organization, it must be exponential. What we mean by this is that the analytics team trains and mentors a small group of early adopters. These power users then facilitate training and mentoring more users, and so forth. So user adoption requires individualized training but becomes an exponential rollout.

Our workgroups and user acceptance testing program is critical not only to self-reporting but to implementation of all of our visualizations. The clinicians and business users who participate in the workgroup also participate in testing the data and the dashboards and reports. This ensures they are expert users. These experts then train and support new business users. This process has been formally established with an enterprise data governance program, and is rolled out in an agile as-we-go process.

V. Results

We have organized a vast number of visualizations into 17 dashboards and reports so far. Each dashboard is really a collection of as many as 20 dashboards, which all interact with each other.

One of our most important success criteria is user adoption. While we started with a pilot of 5 users, we now have 147 active users. Our dashboards have been viewed 31,027 times and are used regularly in clinical and operational meetings.

Our self-reporting initiative has had significant early success. Users have created their own reports and developed programs not mentioned here, including cirrhosis, childhood immunizations, and critical care daily goals. These were developed not by the IT analytics team but by the business users and quality department.

In the future, we plan to performed detailed statistical analysis of clinical outcomes with control sets. However, we have evaluated early progress of the analytics in improving clinician behavior and patient outcomes. In the last 7 months, we have observed the following results vs patient encounters prior to the analytics rollout:

- POKE-R: Reduction in POKE-R events in the PICU by 8.3%.
- Sepsis: 27% reduction in mortality rate, 25% reduction in readmissions, 16 hour reduction in critical care length of stay, 14.6% improvement in antibiotic administration in first 3 hours, 14.8% improvement in timely lactate measurement, reduction in average time to each important clinical action.
- CHF: 60.0% reduction in mortality. 0.18 day reduction in length of stay. 267% increase in order set utilization, 2 hour reduction in time from door to diuretic, 56 minute reduction in median BNP turnaround time, 73% increase in daily weight documentation, 22% increase in followup appointments.
- Pediatric Asthma: 129% improvement in protocol and order set utilization, 0.36 day reduction in length of stay, 11 hour reduction in critical care length of stay, 99.3% steroid administration rate. 57% reduction in time metrics to important clinical events.
- Pediatric Pneumonia: 675% increase in protocol and order set utilization, 30% reduction in readmission rate, 4 hour reduction in average time to first antibiotic administration, 22 hour reduction in critical care length of stay.
- Pediatric Bronchiolitis: 161% increase in protocol and order set utilization, 50% reduction in readmissions, 90% nebulizer compliance rate (5% improvement).
- Blood Utilization: 21% reduction in total blood units administered monthly, 34% reduction in blood units administered without clinical necessity, 7.4% reduction in the percentage of units which are not clinically justified. Total reduction of 5000 red blood cell units administered over 7 months.

We plan to continue to develop new clinical programs, and are currently developing a program for neurology centering on stroke encounters. We also plan to add cost information to the analytics to show the financial value of these improvements. We also plan to do more complete research with control set patient cohorts, to more clearly quantify the program impact.

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