A Physician Partnership: Employing Predictive Modeling and Workload Analysis for CHF Performance Improvement

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In its annual update, the American Heart Association points out cardiovascular disease (CVD) is accountable for one out of every three deaths in the United States. While CVD mortality rates have been steadily declining, the disease burden continues to be high. CVD and congestive heart failure (CHF) remain the first-listed diagnosis in hospitalizations and account for more than 11 million physician visits each year. Needless to say, CVD is a costly disease for hospitals.

Faced with the challenge of improving CHF care, the Quality Team (Q-Team) at Newark Beth Israel Medical Center (NBIMC) undertook an initiative to see if we could improve core measure values and reduce readmissions. We started by focusing on efficiency and analyzing one year's worth of data. We found processes we could positively impact. One issue we uncovered was that some physicians had significant workloads, which was negatively affecting care. In response, a focus on clinical support for physicians, especially with CHF patients, was initiated.

The first focus was on process modification. During research, the Q-Team identified CHF patients with complex medical histories. During implementation, we leveraged Q-Team resources and cognitive capacity to provide an additional resource to physicians with high volume and acuity patients. Cognition is the higher mental process by which we become aware of objects of thought and perception, including all aspects of intellectual capacity such as recognition, comprehension, conception, recollection, reasoning, and judgment. *Cognitive* *capacity* is the total amount of information the brain is capable of retaining at any particular moment. This amount is finite; in other words, the brain's total capacity remains at 100 percent.

Cognitive load is how much of one's cognitive capacity is being used for a particular task at a given time. Since health care is a complex service that requires complex processes, we viewed cognitive capacity as the "thinking capacity" available through the hospital's human resources to think through the complex services involved in the problem-solving and treatment of various CHF cases and scenarios. Use of these extended resources provided more cost-effective interventions in supporting our caregivers and resulted in positive trends in core quality metrics and CHF readmission. Thus, the NBIMC Q-Team and the physicians created a true partnership in the CHF patient health and process improvement effort.

Inspiring Data-Driven Problem Solving

In 2008, like all medical facilities, NBIMC felt the economic pressures and downturn. This financial strain was exacerbated by the costs of treating the uninsured and underinsured. As a result, increasing efficiency and productivity while maintaining quality and safety became even more important goals.

One tool used to achieve these goals was Process Arbitrage, a data mining and modeling methodology. Data mining is the extraction of hidden patterns and predictive information from large data sets. Like statistics, data mining enables predictive factor development that, when combined with focused analysis, allows for *what-if* process improvement scenario testing. The method is based on the concept of managing a health care team's cognitive capacity in clinical processes.

With the mission to discover what current CHF practices could be improved upon, the team faced the challenge of deciding how to deploy limited resources to achieve improvement. Predictive modeling was employed to identify patients most at risk and data derived from that modeling was used to identify opportunities for better care.

Using Process Arbitrage Methodology

Process Arbitrage combines process mining and resource arbitrage. ***Process mining*** is a specialized form of data mining. It creates models (based on timing and event log data, for example) to determine where opportunities for improvement exist in the tasks being performed. ***Resource arbitrage*** is the determination of unique resources and innovative practices that an organization has that have been previously unobserved or underutilized. Thus, use of the Process Arbitrage methodology helps clinicians "mix and match" internal resources and practices to gain a ***comparative advantage***, where certain people can do things better than others at a lower cost or risk.

Process Arbitrage also allows one to examine cognitive capacity consumption in task execution, factoring in the risk of tasks not being completed or completed with errors due to cognitive overload. This data can then be used to determine who can do what better, cheaper and faster.

Starting the Improvement Process with Data Mining

As stated earlier, the initiative was based on techniques documented in the *PEJ.* Author Ragupathy Veluswamy, MD, noted how excess workload can have a negative impact on in-house best practice (IHBP) application and clinical performance. From his findings, Veluswamy denoted how to execute IHBP processes effectively with the available resources of an acute care facility.

Using an extended case log database for physician diagnoses and complexity patterns, physician workload was examined to determine support and improvement opportunities. Our results found an association between heavy workloads and cognitive overload. Based upon these findings, we redesigned clinical processes to allow less acute tasks to be handled by nurse practitioners.

An analysis of baseline data extracted from fourth quarter 2007 through fourth quarter 2008 indicated clinicians with the highest workloads had core measure scores and average Medicare length of stay (LOS) rates that could be improved. This trend has been found in other related research so the Q-Team decided to concentrate on creating processes that supported physicians by reducing their workload in certain areas at certain times.

Enabling Resource Allocation with a Better Predictive Model

Since hospitals must deal with limited resources, knowing when and where to allocate those resources is vital. So, how can a hospital best decide where and how to allocate its resources? To answer that question, we used the Smartgrid lead time analysis tool to redesign the CHF care processes. Figure 1 shows the basis for the process redesign using predictive modeling. Since there is limited time to identify a CHF patient's problems, the risk profile must be decided as early as possible and intervention undertaken before the disease process worsens or the patient is discharged. The modeling highlighted opportunities to improve early intervention. In this case, we were able to reduce staff man minutes 67 percent.

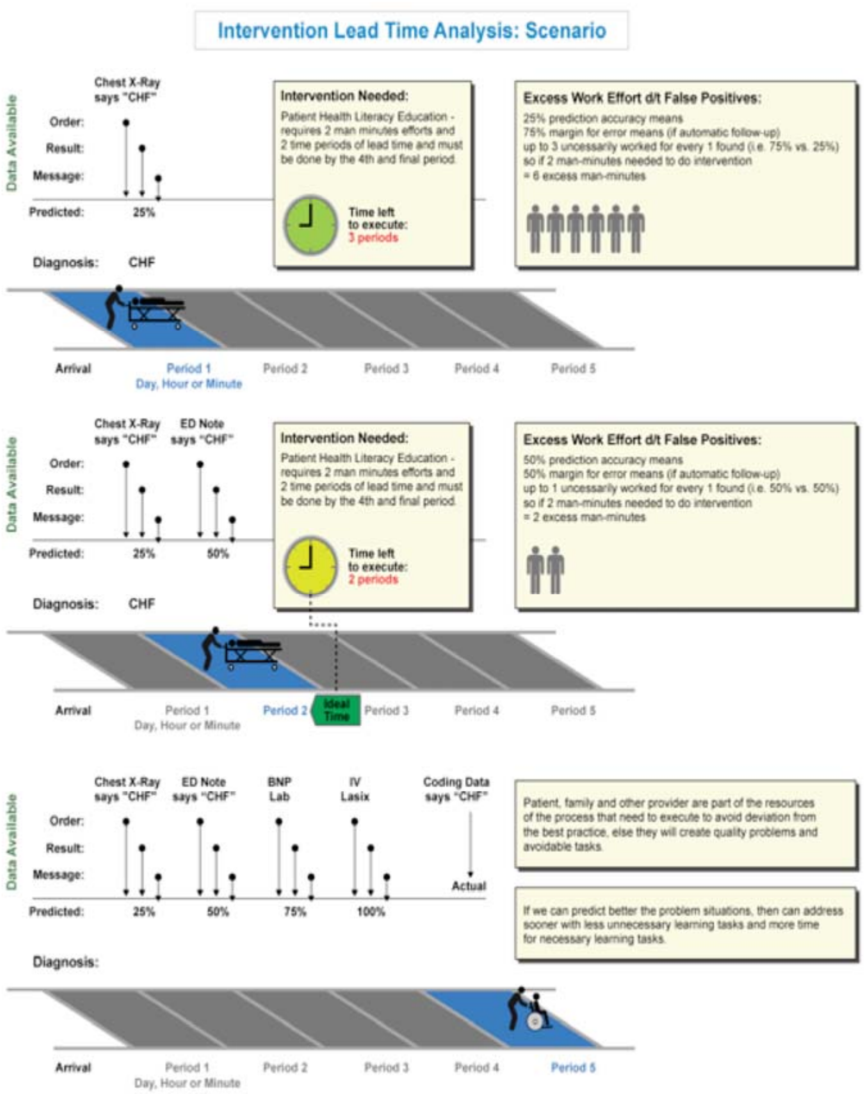

Figure 1. Analysis of intervention lead time using the Healthcare Smartgrid Intervention Lead Time Analysis predictive modeling tool. The visual highlights the ideal time for CHF intervention to maximize cost-effectiveness.

To guide the Q-Team toward the right patients and support doctors proactively, we needed a daily predictive modeling process. Figure 2 illustrates the model used for CHF prediction.

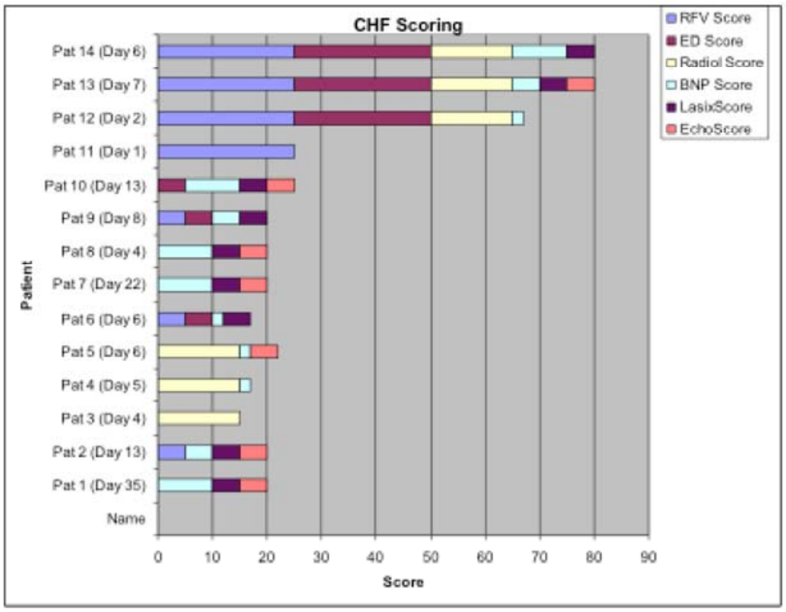

Figure 2. A graphical representation of the scoring model used for CHF prediction. Note the scoring includes several data sources to provide a complete picture.

In creating the score, we first compiled available data sources that may indicate CHF. These were evaluated by weighting for various factors (e.g., IV Lasix order from the data source “medication orders” scored 10, while BNP labs greater than 600 added 10 and was “stacked” on it to the right). These factors were mined from electronic data sources then put into a table, where simple keyword searches or “if-then” formulas could be done in a tool as simple as Microsoft Excel to create graphs. Other data sources included ADT reasons for visit (RFV), ED, H&P, and radiology dictations. Searches for negations also gave negative weights to reduce scores (e.g., no evidence of CHF). We chose to sort the list by unit, then date of admission, with highest score at top.

To fine tune and improve weights and cut-offs, the scores were compared over time to the final coded ICDs of patients scored. This comparison minimized false negatives (where the model misses a real CHF case principal diagnosis – so, if 100 cases were coded as CHF and 90 were predicted by the model but 10 were missed, this would be a 90 percent accuracy for false negative), and false positives (where the model claims the case is CHF when the coders decided it was not a principal or secondary diagnosis – so, if 180 cases were predicted by the model, but only 90 cases were actually coded CHF, this would be a 50 percent accuracy for false positive). At these accuracy levels and by bringing more data (e.g., dictations) into the model faster, the team did less work and the work they did was more effective. This reduced the number of man-hours, and thus people needed, to provide quality care without increasing costs.

Achieving Quality Results

From this work we were able to highlight the relationship between cognitive overload and clinical quality. Predictive analysis and modeling demonstrated the greatest improvement opportunity that can come from assisting the busiest doctors managing the most complex cases. Overall, the initiative enabled NBIMC to deploy effective, efficient new processes producing tangible results in patient care quality: (a) NBIMC's publicly reported core measure metrics *improved* as shown in Figure 3, and (b) the process redesign produced improved core measure outcomes that have been *sustained.*

Overall Improvement in Core Measures and LOS
Starting 2008 Implementation of Healthcare Smartgrid®

ITEM	2007	2008	2009	2010	2011
Total Cases	N/A	330,369	297,743	319,998	326,588
CHF Cases	N/A	2,412	2,565	2,977	2,801
Percentage CHF of Total	N/A	0.73%	0.86%	0.93%	0.86%
HF Appropriate Care Score	99.2%	100.0%	100.0%	100.0%	100.0%
PN Appropriate Care Score	81.2%	92.6%	100.0%	(est. 95%)	(est. 98%)
AMI Appropriate Care Score	94.1%	98.2%	100.0%	100.0%	100.0%

Figure 3. A table of core measure improvements. Note that core measures improved significantly once given processes were redesigned and enabled using the Process Arbitrage method.

Additionally, with attention being expanded to readmissions with an added focus on education and care coordination with the primary care physician (PCP), the 2011 data showed an overall CHF readmission improvement rate of 33 percent for the year. Consequently, as Figure 4 illustrates, over the 6-month period from June to December, there was a 50 percent peak-to-trough drop in CHF readmission.

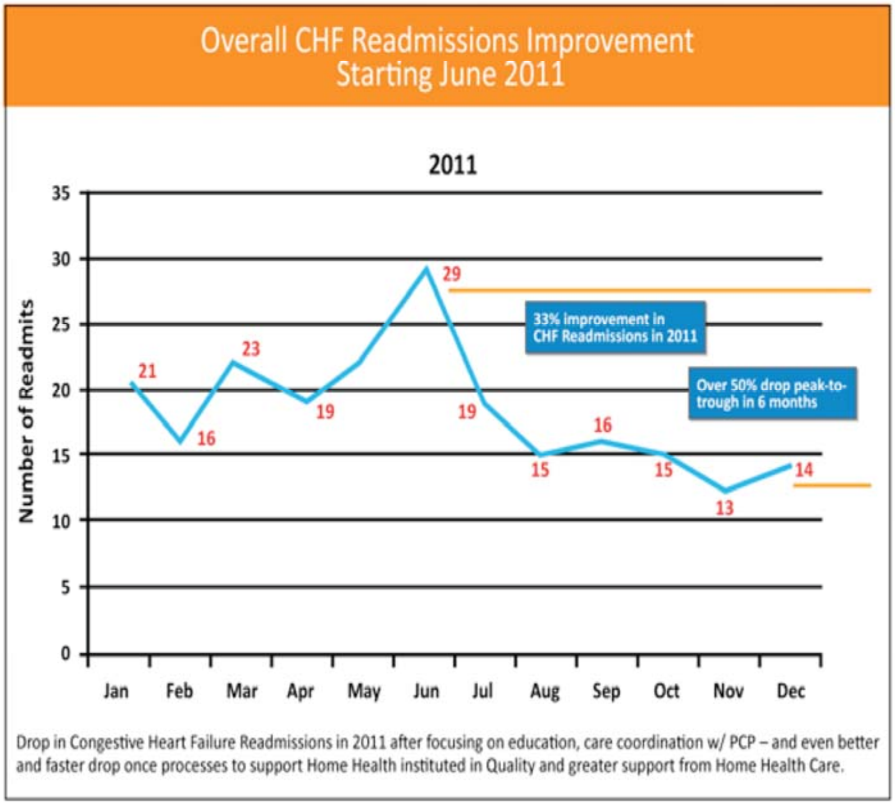

Figure 4. An illustration of the improvements in NBIMC's CHF readmissions for the year 2011.

Moreover, not only was there an overall CHF readmission drop, but positive trends were increasing while poor trends were decreasing, as shown in Figure 5. To make CHF readmissions easier to examine and study, we categorized them into six different classifications:

- Category 1 included patients who were only admitted once for CHF and would not be coming back under that diagnosis.
- Category 2 included patients who were admitted to the hospital with CHF, but their time between readmissions was increasing.
- Category 3 included patients who were stable and not decreasing time between readmissions. The natural state of a CHF patient is typically to get readmitted more frequently over time as his or her heart deteriorates.
- Category 4 included patients who were decreasing days between readmission, but had not yet dropped below the 30-day mark.
- Category 5 included patients who were decreasing days between readmission, but started at above 30 days and subsequently dropped to below the 30-day mark.
- Category 6 included those patients who were not improving despite all of our best efforts, and continued to drop below the 30-day readmission point.

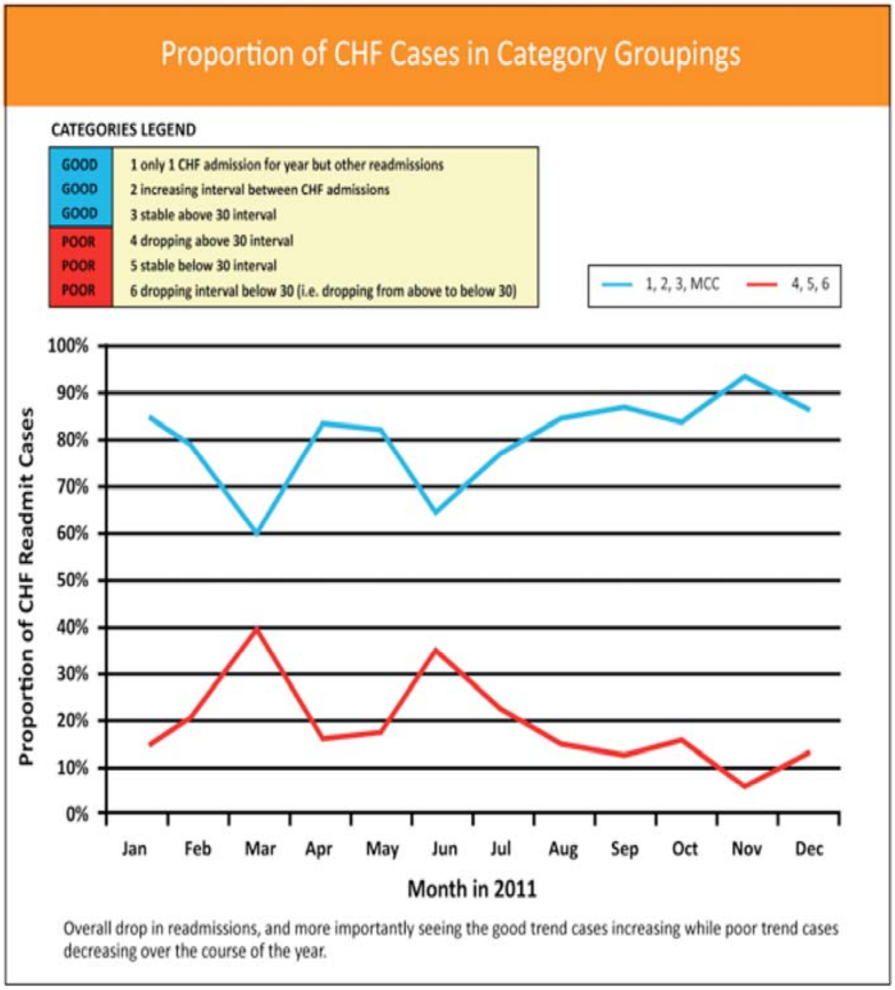

Figure 5. An illustration of the CHF by category demonstrating the increase in good and decrease in poor trend cases.

The increase in positive trend can be explained by our policy of educating patients and families upon diagnosis and, based on level of risk, devoting more resources to those patients. One crucial finding was that when caregivers were trying to educate patients for compliance, if the caregiver was overloaded (i.e., too many tasks needing to get done in too little time), he or she became impatient. This was sensed by patients, which caused them to become more anxious in getting through the education quickly and stating they understood the information - even if they did not really understand or would likely not remember once discharged. Thus, it was important to ensure caregivers had sufficient cognitive capacity to provide the education without undue stress or impatience.

Also part of this new approach was to identify and contact the PCP to make a follow-up appointment within two weeks of discharge. Figure 6 demonstrates the importance of PCP follow up. If there was no follow-up before the ***tipping point***, which we confirmed to be the 15th day post discharge, there usually was a readmit. However, once the PCP ***breakthrough*** was discovered and follow-up became standard procedure, a ***positive cycle*** developed that reinforced seeing the PCP rather than the emergency department inside the 30-day window. This reduced readmissions.

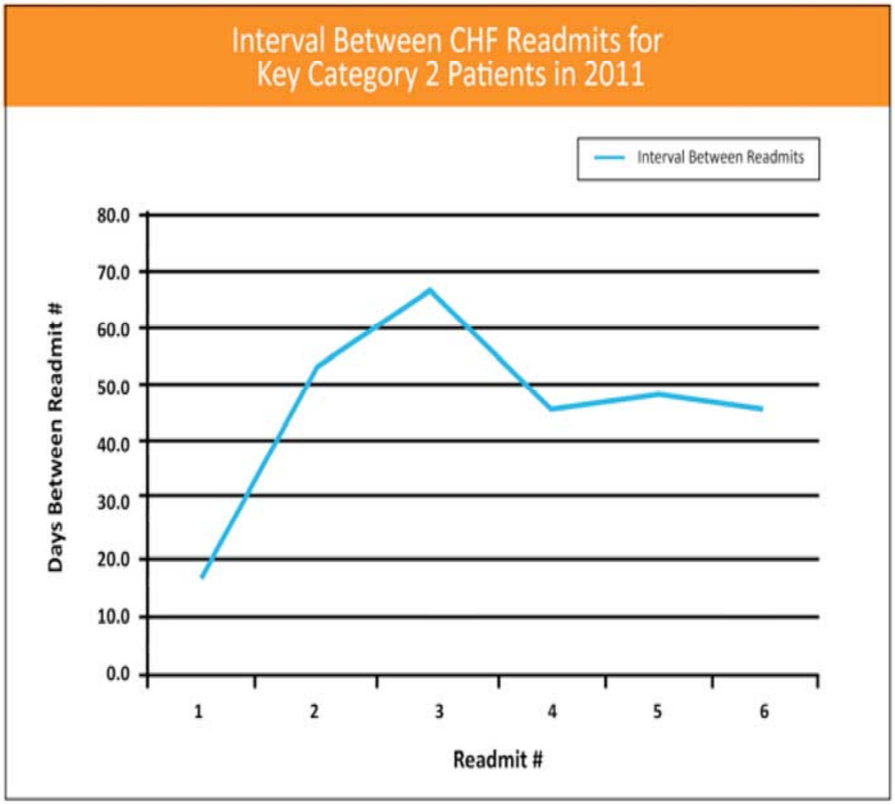

Figure 6. An illustration showing the interval between CHF readmissions for key Category 2 patients during 2011.

Leveraging Physician Strengths is the Conclusion

Using available technology and systems, we achieved these results because clinicians' cognitive capacity was proactively leveraged by their respective teams and because they had decision points prioritized for them based on algorithms they helped to develop. This ensured non-critical actions were automatically carried out by other providers so physicians were not being overwhelmed by unnecessary decisions. We analyzed clinical actions/inactions every 24 hours and from that, created work lists that directed the Q-Team toward specific patients. We also engaged physicians in routine chart review. There were two important components to this: (a) a focused review of patients at risk for not receiving a clinical intervention, and (b) the provision of feedback to clinicians within 24 hours. With the improvement in quality came a reduction in complications, readmissions, and ultimately, costs. The methods focused on improving cost-effectiveness through comparative advantage, which could be modeled proactively to ensure success of the team and their processes.

The reduction in staff work due to more accurate predictive models showed us that efficiency was created. Because of the contributions made by this initiative, NBIMC now enjoys a focused approach to efficiency, quality and fiscal discipline. It truly takes a partnership of dedicated quality practitioners working with physicians: NBIMC currently has publicly-reported quality measures that have put it in the top 10 percent of the state.

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