Carolinas HealthCare System

Reducing Readmissions: Harnessing the Power of Predictive Analytics

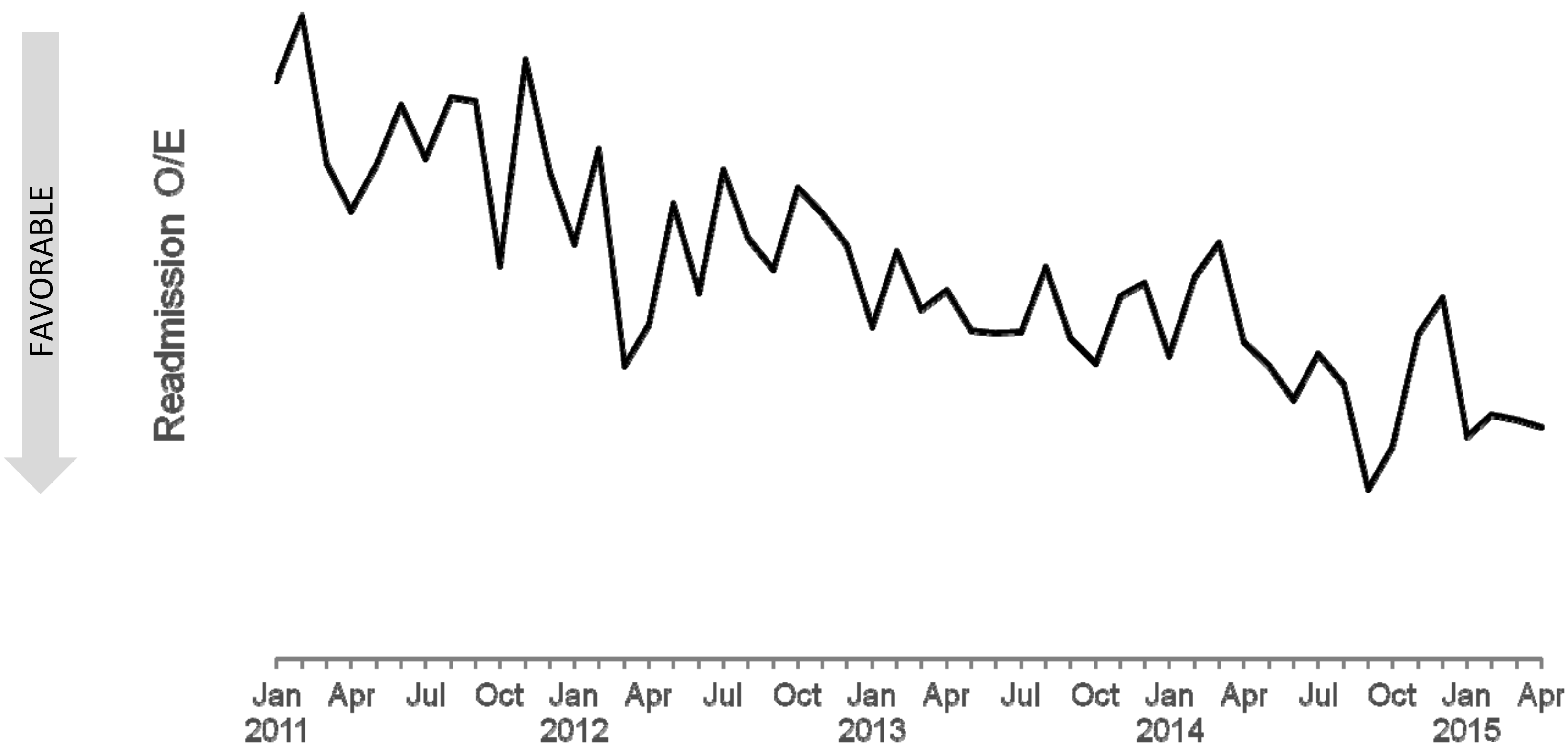
Jean Wright MD MBA

VP, Chief Innovation Officer &

Interim Analytics Officer

One

Carolinas HealthCare System
Journey to Reduce Avoidable Readmissions

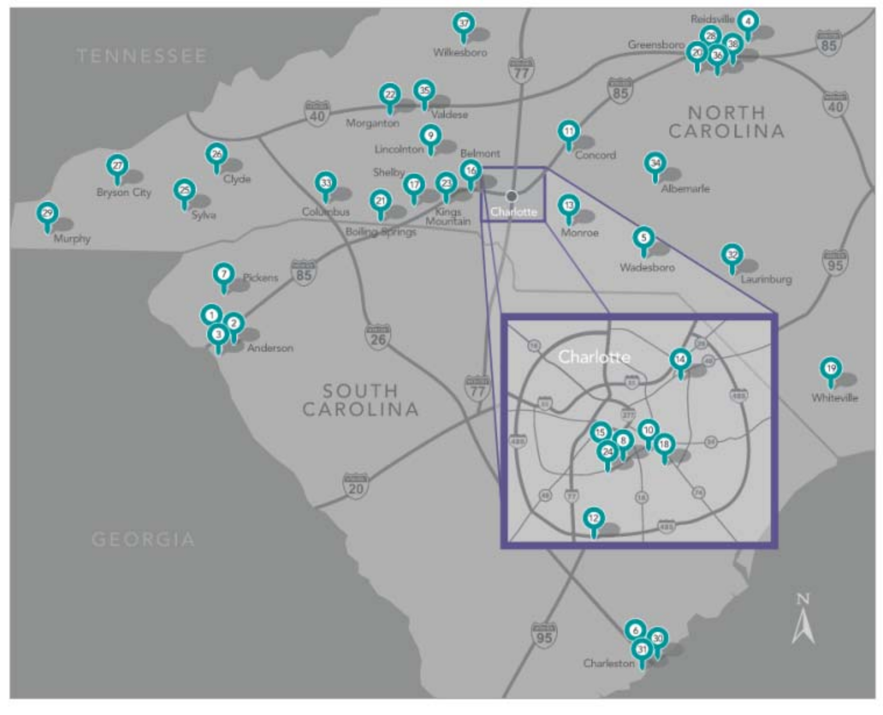


*Updated 7/14/2015

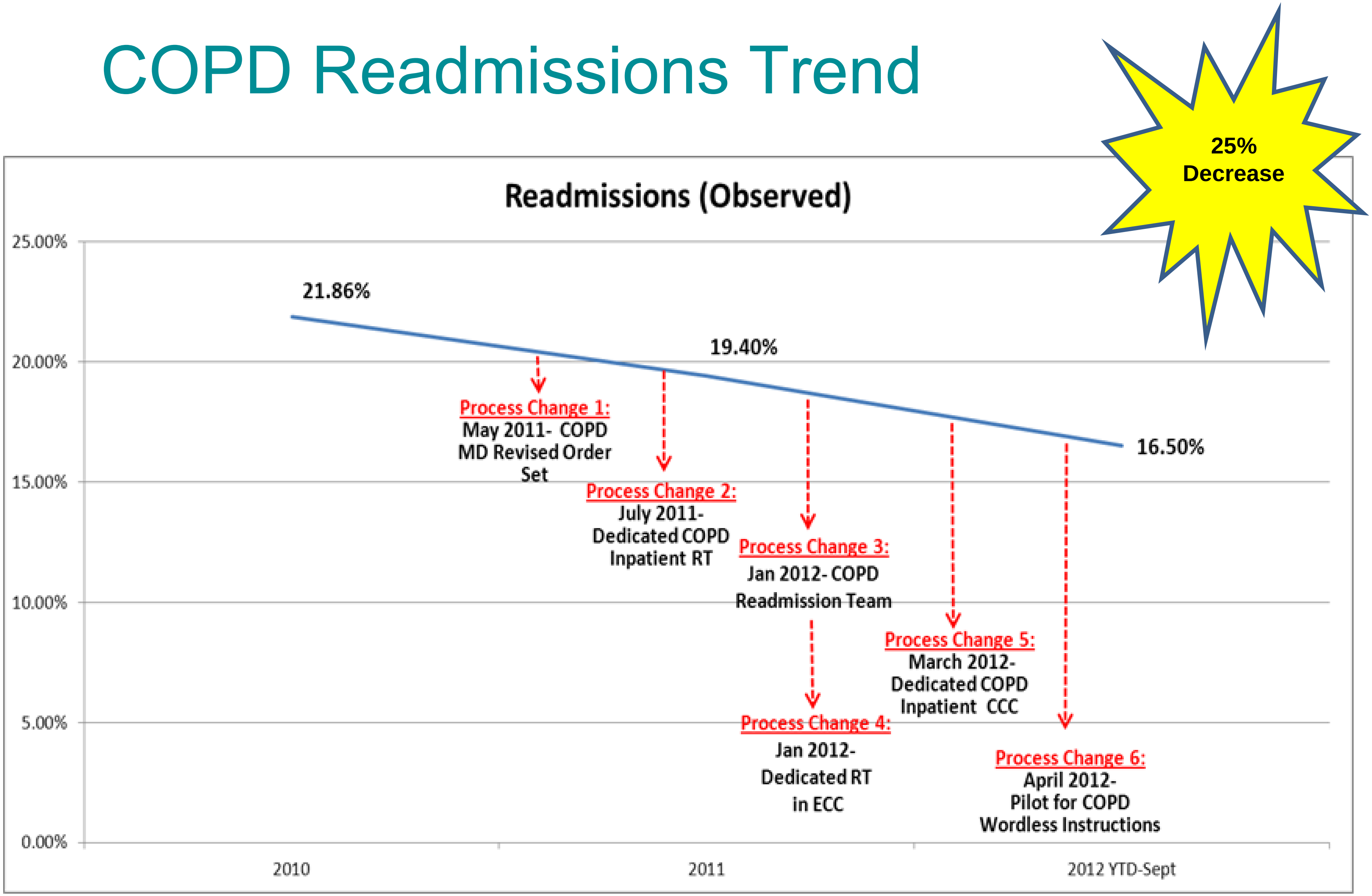
Carolinas HealthCare System

Carolinas HealthCare System is one of the leading healthcare organizations in the Southeastern United States and one of the largest public not-for-profit systems in the nation

- 60,000 Team Members
- 7,400 Licensed Beds
- 900 Care Locations
- 10 Million Patient Encounters
- HEN / LEAPT Contractor
- Dixon Advanced Analytics Group



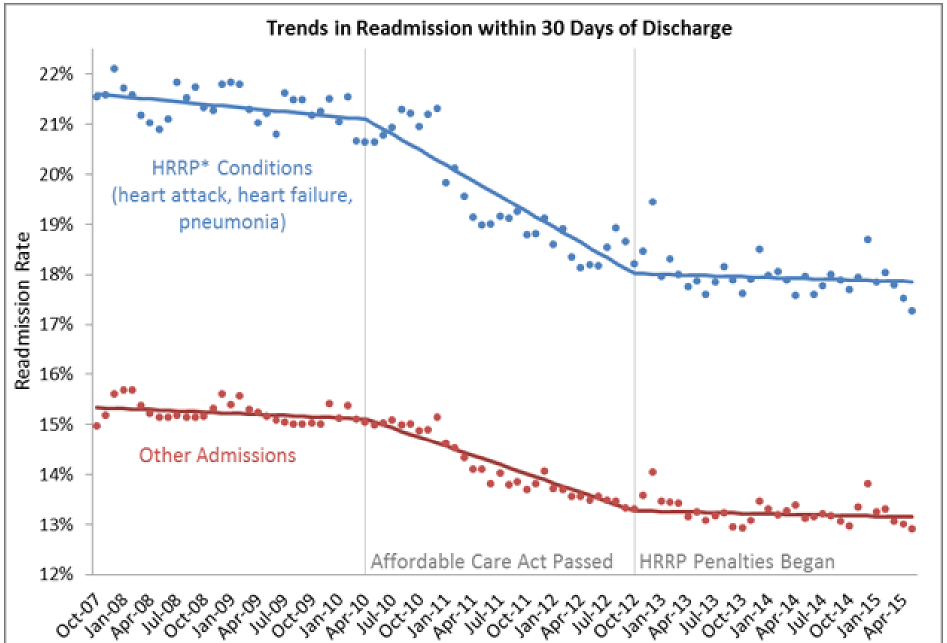
COPD Readmissions Trend



MS-DRG: 190:Chronic obstructive pulm disease wMCC, 191:Chronic obstructive pulm disease wCC, 192:Chronic obstructive pulm disease w/oCC/MCC

Nationally, 3 years of penalties, 3 years of pain

- FY 2016, 2,620 facilities are being penalized.
- The highest penalty for a single facility is over $3.6M.
- 49 hospitals are being penalized at least $1M in FY 2015.
- 38 hospitals are receiving the maximum 3% penalty



*HRRP: Hospital Readmissions Reduction Program. Heart attack, heart failure, and pneumonia were used in the program beginning in October 2013. Chronic obstructive pulmonary disease and hip and knee replacement were added in October 2015 and are not included in this graph.

Readmissions will cut Medicare payments to some Charlotte hospitals

Recommend 15 people recommend this. Sign Up to see what your friends recommend.

By Karen Garloch and Jordan Rau
Kaiser Health News

Posted: Sunday, Oct. 05, 2014

Some Charlotte-area hospitals will receive reduced payments from Medicare next year, the third year of a federal program that penalizes hospitals for having too many patients readmitted for additional treatment within 30 days of their last hospital stay.

Since 2012, the federal Medicare program for seniors has penalized hospitals that have higher-than-expected readmission rates among patients treated for three medical

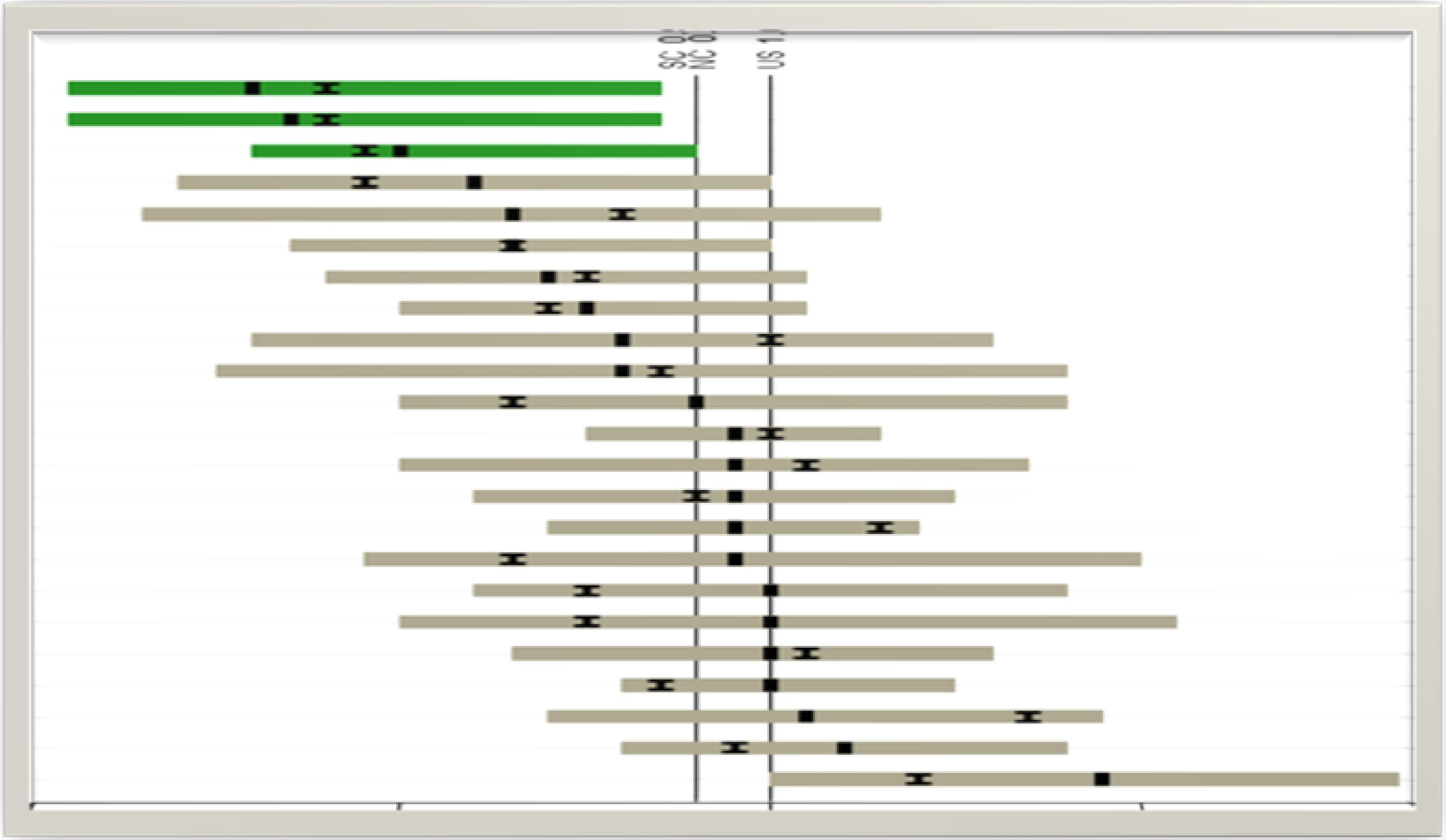
MORE INFORMATION

FINES FOR CHARLOTTE-AREA HOSPITALS

The following figures compare fiscal year 2014, which ended Sept. 30, to fiscal year 2015, which started Oct. 1.

Hospital	FY 2014	FY 2015
CMC-Pineville	0	0
Novant Health Presbyterian Medical Center	0.18 percent	0.30 percent
Novant Health Huntersville	0.08	0.10

Hospital Wide Readmissions Standardized Readmission Ratio



Do the Math

Base Operating DRG Payment Amount:

[[case mix index × ((labor share × wage index) + (nonlabor share x COLA))] + new technology payments, if applicable] × total Medicare cases

[[1.3656 × ((3,804.40 × 1.0537) + (1,661.69 x 1))] + 0] × 5,433 = 41,852,953

To estimate a hospital's total readmission penalty, the Medicare case-mix index can be used in place of the DRG weights for each case

Readmissions Payment Adjustment Amount:

(base operating DRG amount for all admissions × readmissions adjustment factor) – base operating DRG amount for all admissions

(41,852,953 × .9765) – 41,852,953 = (983,544)

Carolinas HealthCare System

If readmission penalties are appropriate for healthcare, why not for other groups?


Home › OP-ED › Why Prisons Should Try Readmissions Penalties

OP-ED THCB

Why Prisons Should Try Readmissions Penalties

Aug 19, 2015 4

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By STUART M. BUTLER

By the end of 2013 there were approximately 1.5 million people in state

Driving Forces for Predictive Analytics in Healthcare

"Skyrocketing costs have rendered the current U.S. healthcare system 'unsustainable,' market forces are calling for a performance-based system, analytics are crucial to this paradigm shift from 'volume' to 'value,' and the transformation is inevitable."

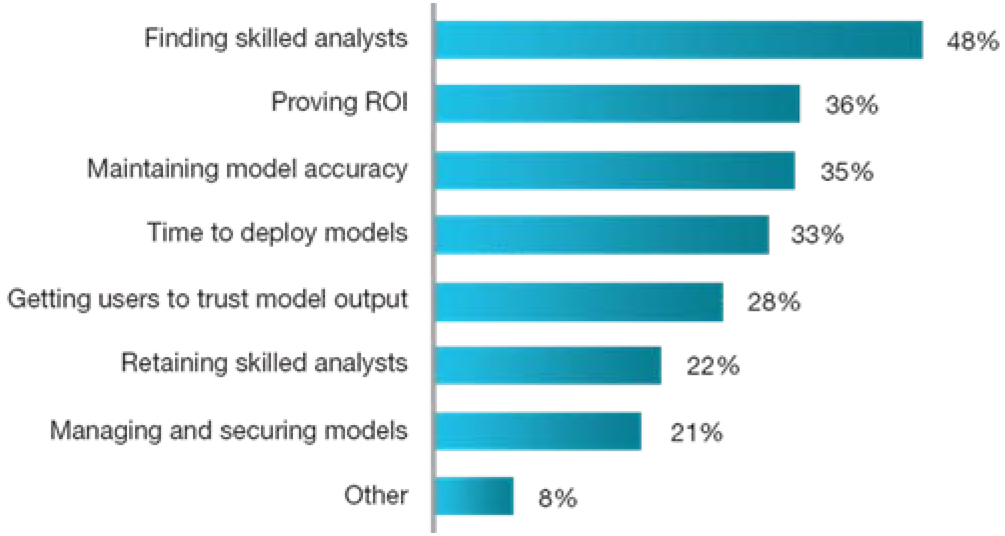
Healthcare: the quiet reform by Peter Horner
Analytics Magazine, Jan/Feb 2012

1	BI/Analytics
2	Infrastructure and Data Center
3	Industry-Specific Applications
4	Cloud
5	Mobile
6	ERP
7	Networking, Voice and Data Communications
8	Innovation and Growth
9	Application Development
10	Integration
11	Compliance
12	Customer Relationship Management

Source: Gartner March 2014
Analyst(s): Zafar Chaudry, M.D. | Steve High

Challenges in Deploying Predictive Analytics

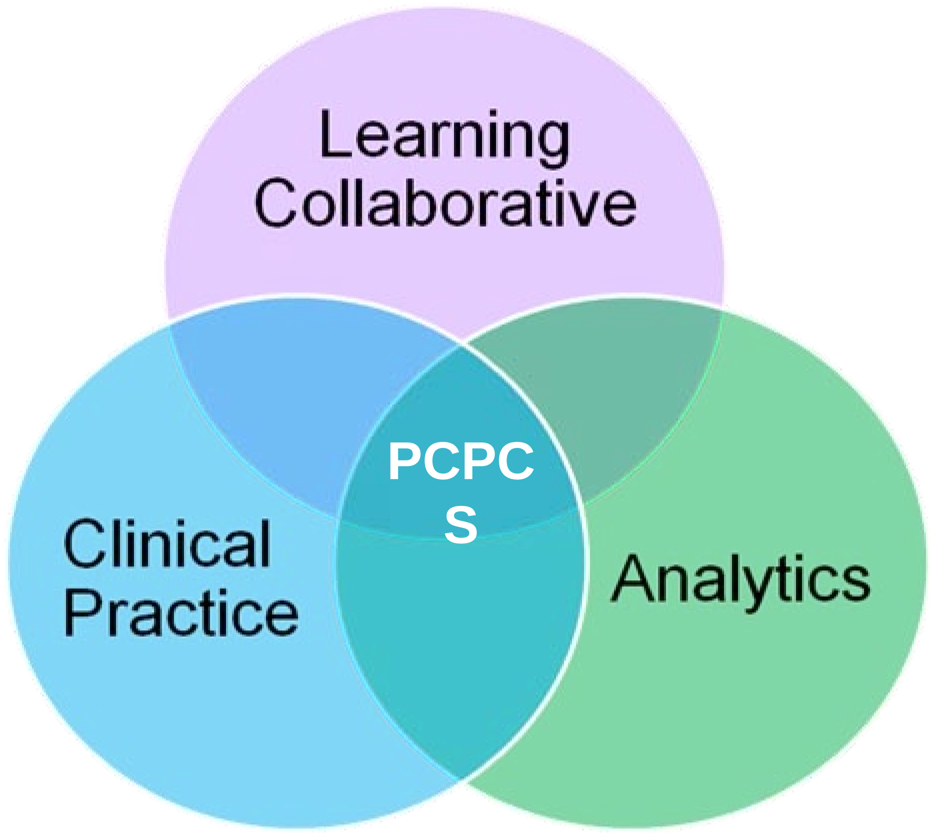
"Despite the buzz, the percentage of organizations that have implemented predictive analytics has remained surprisingly flat."



Wayne Eckerson, Principal Consultant
Eckerson Group

PROJECT VISION

Patient-**C**entered, **P**oint of **C**are Clinical Decision **S**upport



Project Vision

Carolinas HealthCare System

Predixion Software

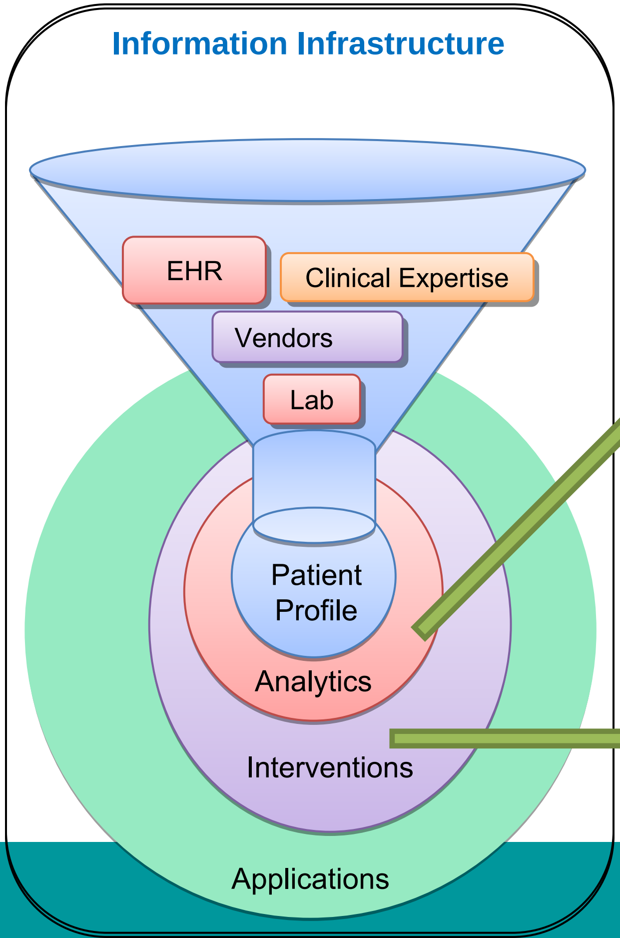
"We will analyze health and consumer data for insights into individuals' clinical risks and through the CHS Learning Collaborative…

…enable the best intervention and treatment decisions at the point-of-care…

…that optimize quality and cost-effective health services."

Analytically-driven, personalized care delivers value

Leverage our information infrastructure



Build highly predictive model

Within & out of hospital:
- Improve care quality
- Increase coordination
- Target resources on high risk patients

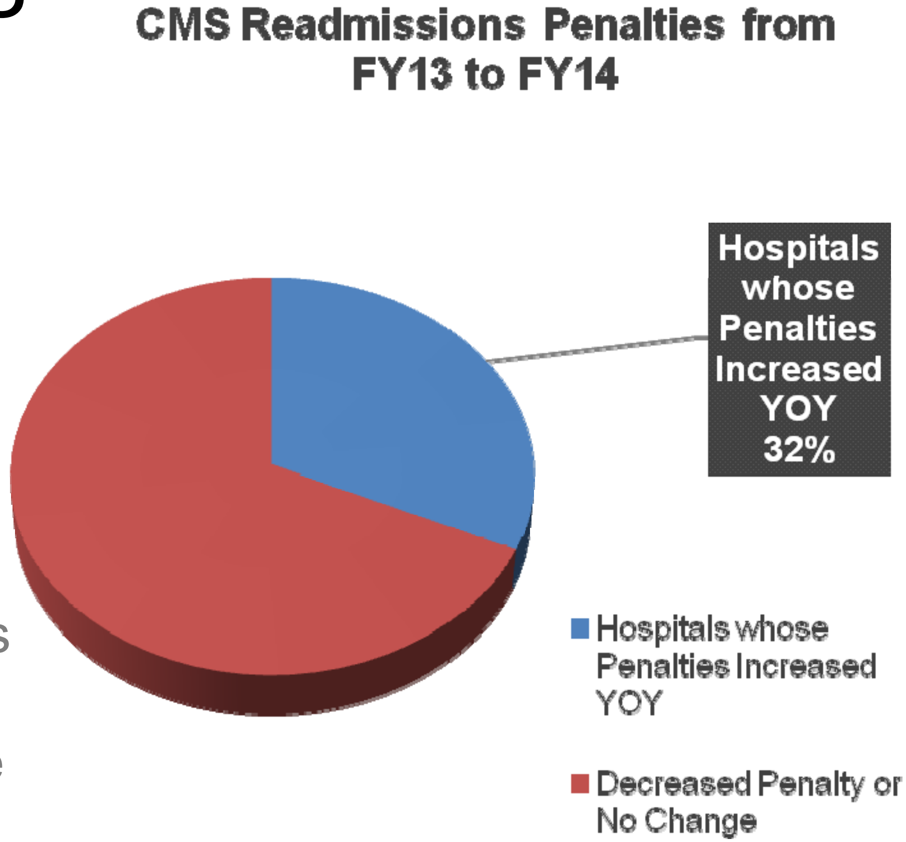
Addressing The Readmissions Challenge

Project Goal: Our Problem

Identify patients at risk of readmitting *before* they leave the hospital and enable care providers to intervene

Project Goal: Your Problem

This goal is important to CHS, but it is important to every other hospital that faces penalties related to preventable readmissions



Source: Kaiser Health News analysis of data from the Centers for Medicare & Medicaid Services.

ANALYTICS

2 Years of Discharges

9 Hospitals

100,000 discharges

Analytics: Risk Models Attributes

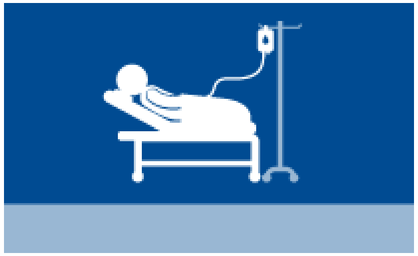
- Risk models predict a patient's individual risk for

  - 30-day, unplanned readmission

  Defined using CMS methodology
- Used 2 years of historical data from 9 Metro hospitals to build the model.
- The primary data source is the EMR (EDW)
  - Pulling over 70 predictive fields hourly, from the first hour admission, through the last hour of the stay
  - Continuously updated as the patient's condition changes.

The risk score changes throughout the stay

Admission on Monday



Diagnosis: Stroke

High Risk
20%

Complication on Tuesday

Aspiration
Pneumonia

Very High
Risk
50%

Key Predictors of Readmission Risk

Demographics

Age
Race Code
Insurance
Hospital Name
Service Provided
Admission Type
Transfer Type

Co-morbidities

Primary Diagnosis
Any Malignancy
Cerebrovascular Disease
Charlson Comorbidity Score
Chronic Pulmonary Disease
>9 Meds and >9 Problems
End Stage Renal Disease
Cancer Cohort
Myocardial Infarction
Number of diagnoses in the problem list
Number of orders
Pulmonary Disorder
Solid Tumor without Metastasis

Psychosocial

Clinical Nutrition Consult
Living Situation
Need Transportation Assistance
Physical Therapy Consult

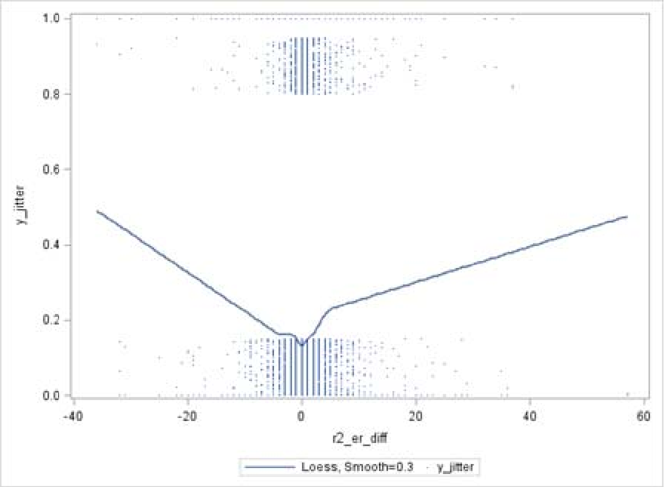
Utilization

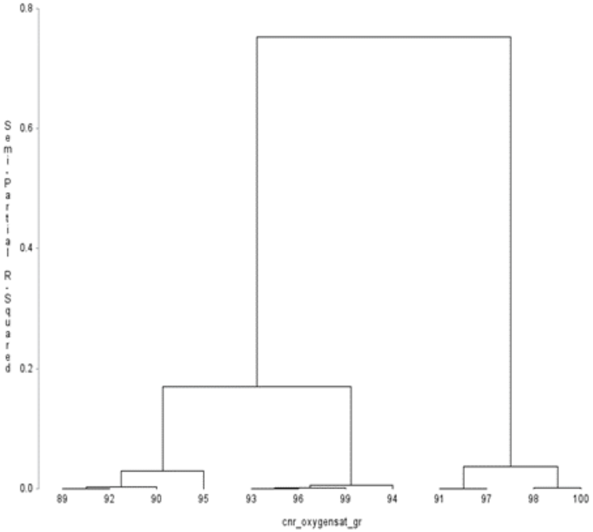
Days since last discharge (w/in 6 months)
Number of Inpatient visits in the last 6 months
Number of ED visits in the last 6 months
Number of Transfers
Discharged to home in the last 30 days

Continued…

Building the model

- Variables were gleaned from the literature and from clinicians
- Variables were analyzed for their impact either
  - as a continuous variable,
  - or a categorical variable
- The model was then tested in a variety of ways to assure is functionality
  - Build versus test cohorts
  - Bootstrap methods



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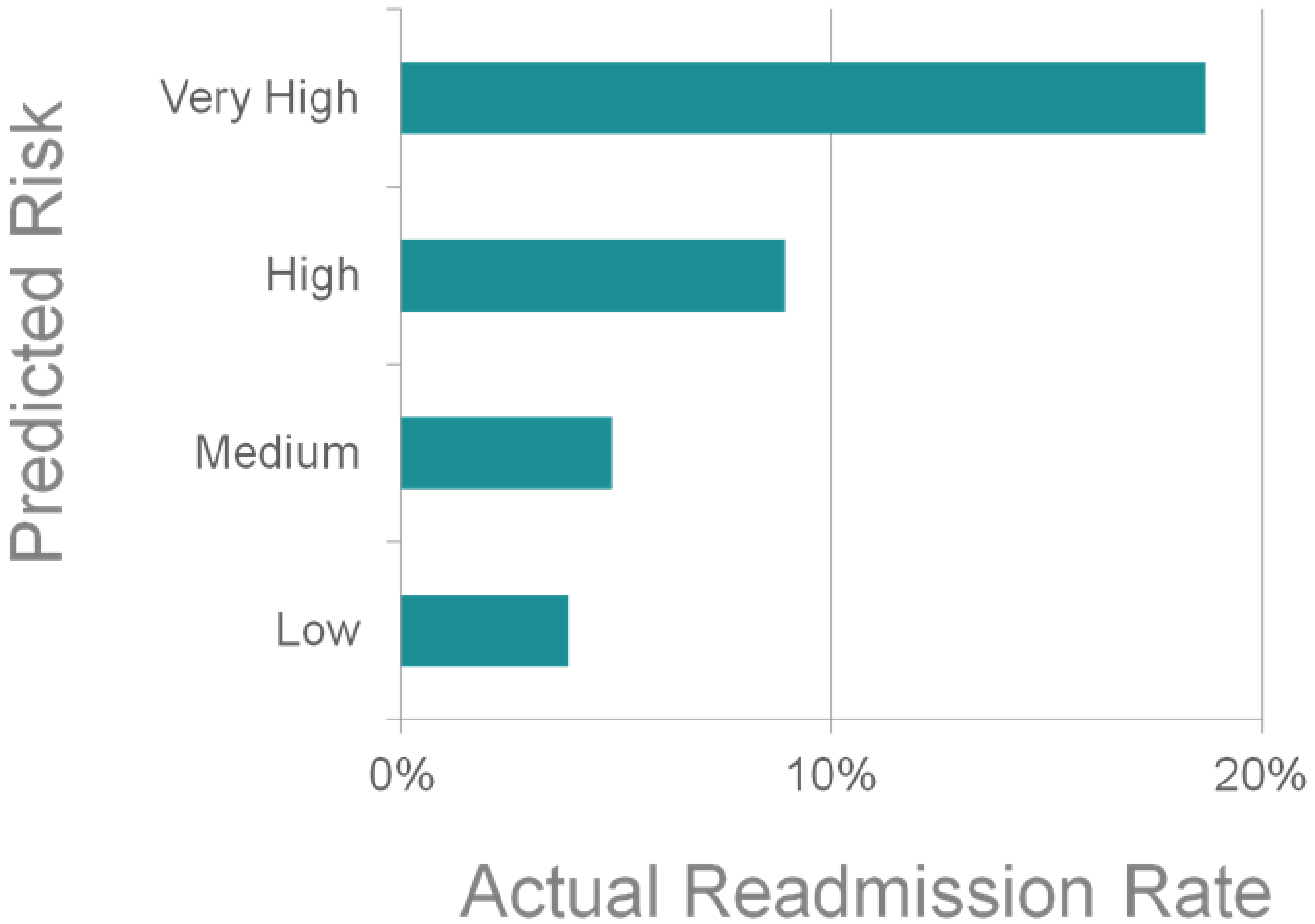
KitchenAid
KitchenAid

Analytics: Risk Model Accuracy

- Model Accuracy: C-stat = 0.77
- PCS Readmission model is better than any other predictive models in published literature
- C-stat is the area under the red curve. Accuracy increases as the curve moves towards the upper left corner away from the orange line, which represents a random guess (e.g., coin flip).

Validation of Readmission Risk Model

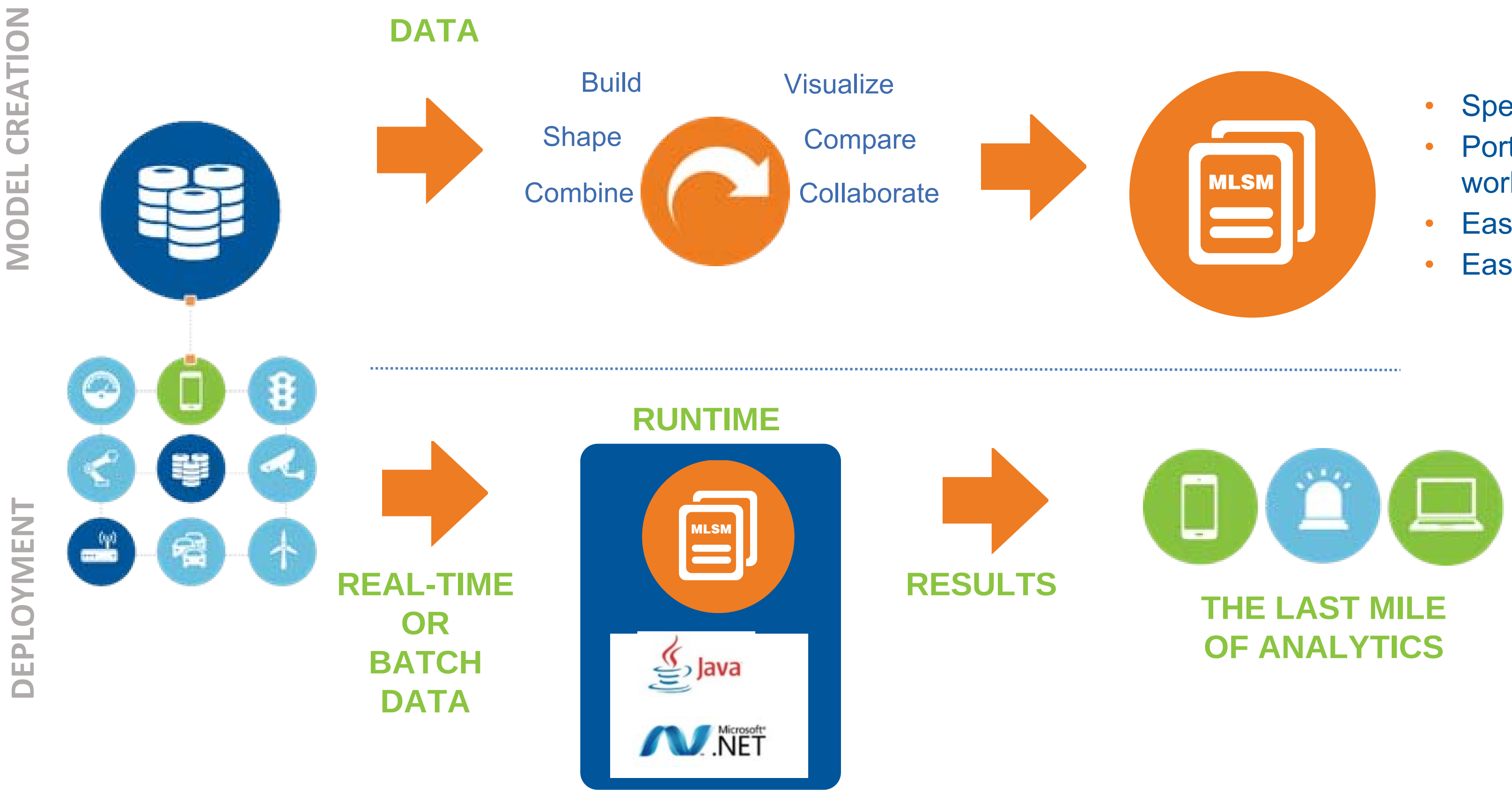


Industry Interventions

- Case managers can target high risk patients and apply standard care plans (interventions)
- Create ability to measure and track the effectiveness of the intervention (continuous feedback cycle)

INTERVENTION TYPE	INTERVENTION DESCRIPTION	EFFICACY
Hospital Based	Dietary Consult	15%
	Smoking Cessation	15%
	Diabetic Teaching	15%
	Pharmacy Consult	15%
	Palliative Care	30%
Telehealth	Telehealth	60%
SNF	Skilled Nursing Facility	
Acute Inpatient Rehab	Acute Rehab	
LTC Hospital	Long Term Acute Care Facility	
Hospice- Facility	Hospice Facility	40%
Home Care	Home Care- Skilled Need	25%
	Home Visit RN Med Mgt/SW	50%
	Home Infusion	
	Home Equipment	
	Home Oxygen	
	Telemonitoring	14-80%

Patent-Pending MLSM Provides Value in Model Creation & Deployment



- Speed to value
- Portable analytic workflow
- Easy to embed
- Easy to update

Carolinas HealthCare System

Units Scenario Manage Welcome Richa Shah!

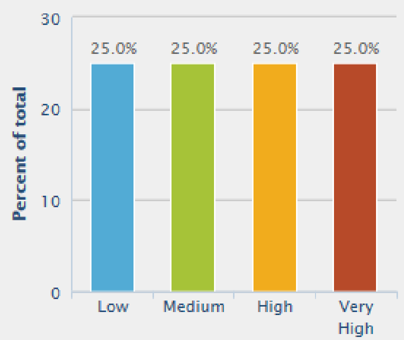
Patient Centric Solution

SEGMENTS

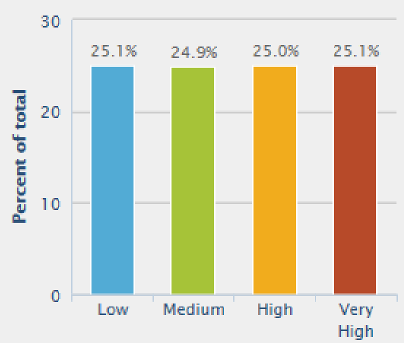
All

Readmission LOS

READMISSION RISK BANDS



LOS RISK BANDS



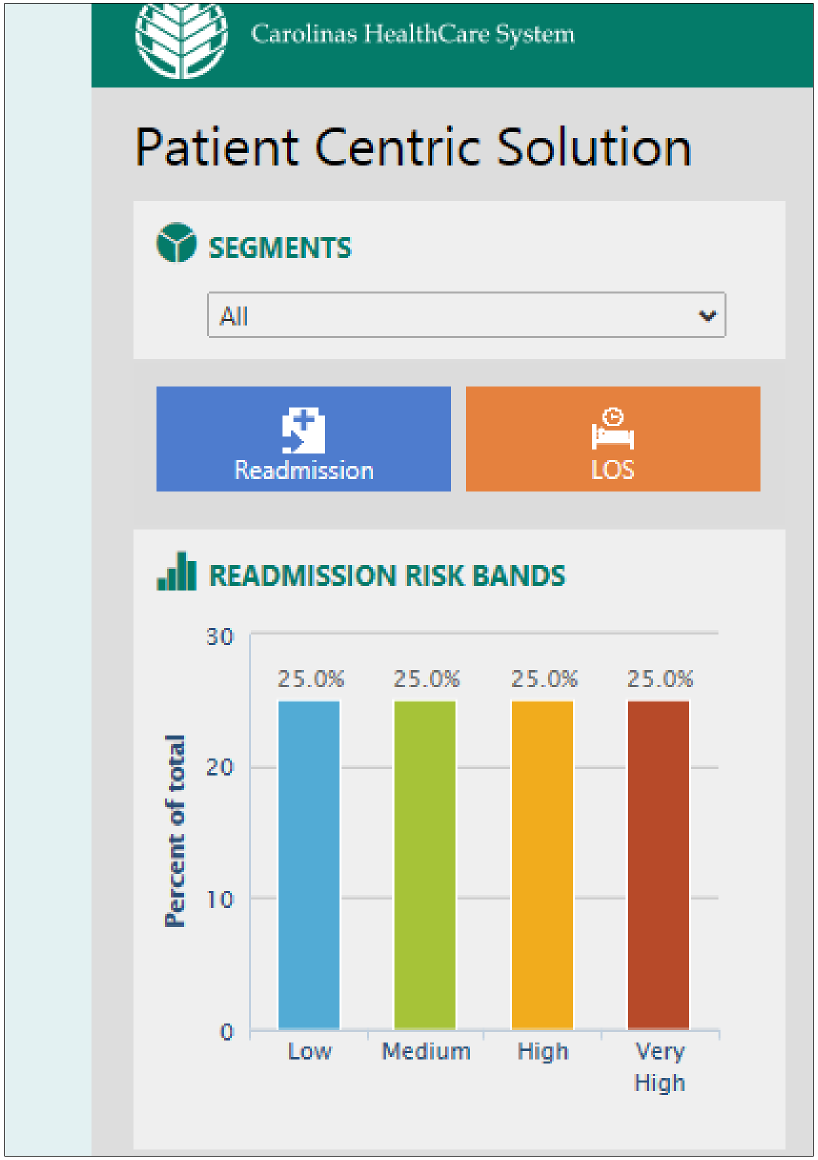
180585 items Show Admitted Print Export

						Risk Band			
	Unit	Patient ID	Account	Patient Name	Roo...	Readmission	LOS	Intervention Modifie...	Intervention
→	PX Unit-D-07	10500		Patient PX-10...	000	Low	High		
→	PX Unit-B-06	11000		Patient PX-11...	000	Very High	High		
→	PX Unit-B-06	11500		Patient PX-11...	000	Medium	Medium		
→	PX Unit-D-06	12000		Patient PX-12...	000	Low	High		
→	PX Unit-D-06	12500		Patient PX-12...	000	Medium	High		
→	PX Unit-B-06	13000		Patient PX-13...	000	High	High		
→	PX Unit-A-02	13500		Patient PX-13...	000	Low	High	Thomas Wells	Oct 30, 2014
→	PX Unit-D-06	14000		Patient PX-14...	000	Low	Very High		
→	PX Unit-D-06	14500		Patient PX-14...	000	Low	High		
→	PX Unit-B-06	15000		Patient PX-15...	000	Medium	High		
→	PX Unit-A-02	15500		Patient PX-15...	000	High	High		
→	PX Unit-B-06	16000		Patient PX-16...	000	Low	Medium		
→	PX Unit-G-06	16500		Patient PX-16...	000	Very High	Low		
→	PX Unit-G-05	17000		Patient PX-17...	000	Medium	Low		
→	PX Unit-D-06	17500		Patient PX-17...	000	Low	Medium		
→	PX Unit-B-06	18000		Patient PX-18...	000	Very High	Medium		
→	PX Unit-G-06	18500		Patient PX-18...	000	High	Very High		
→	PX Unit-A-01	19000		Patient PX-19...	000	High	Low		
→	PX Unit-E-01	19500		Patient PX-19...	000	Medium	Low		
→	PX Unit-B-06	20000		Patient PX-20...	000	High	Very High		

1 2 3 4 5 6 7 8 9 10 ... 20 items per page 1 - 20 of 180585 items

Scenario: Default Scenario **Version:** 1.0.0.100

Predixion

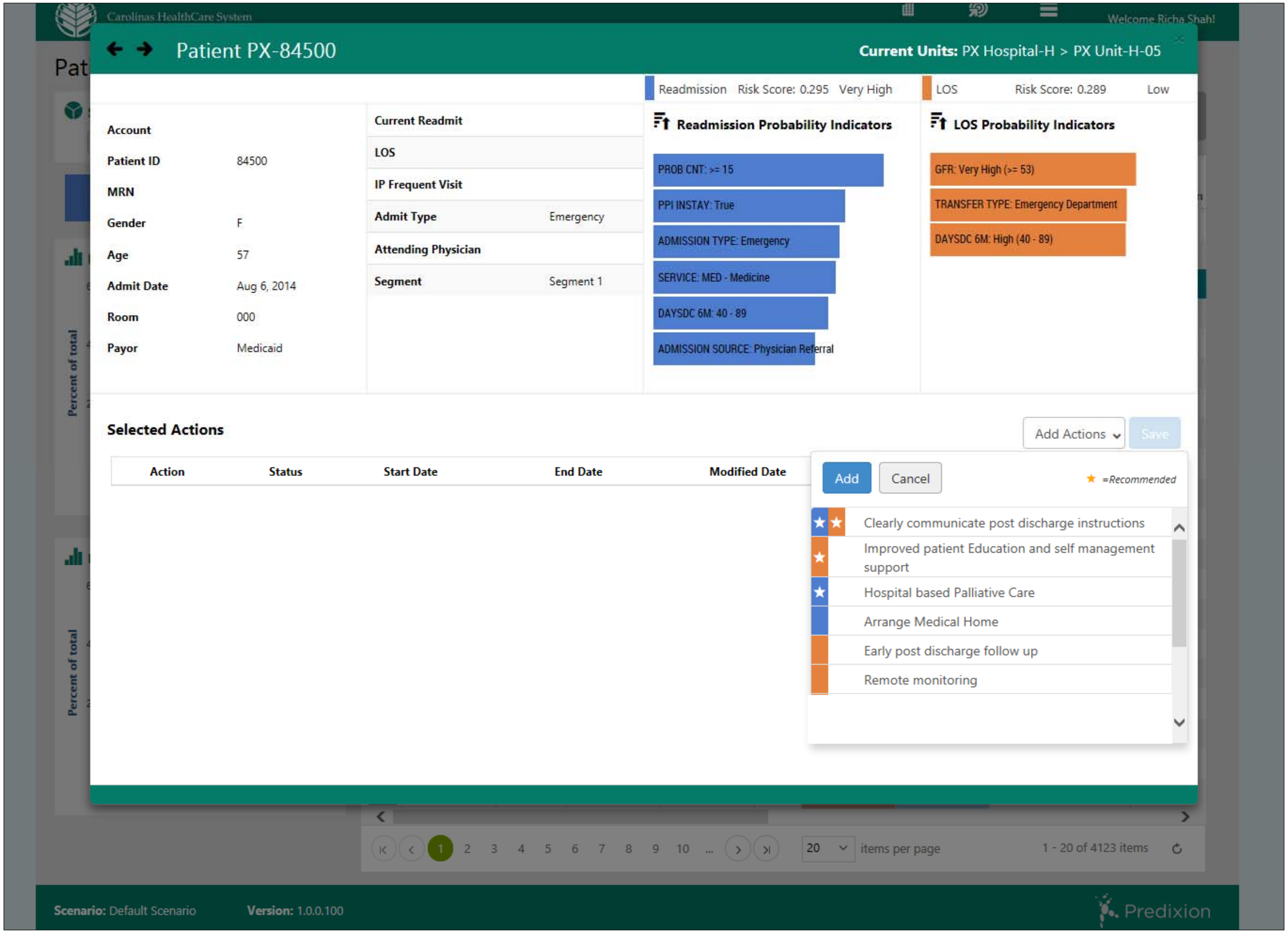


How do my patients look compared to others?

Patient Name	Roo...	Risk Band	
		Readmission	LOS
Patient PX-10...	000	Low	High
Patient PX-11...	000	Very High	High
Patient PX-11...	000	Medium	Medium
Patient PX-12...	000	Low	High
Patient PX-12...	000	Medium	High
Patient PX-13...	000	High	High
Patient PX-13...	000	Low	High
Patient PX-14...	000	Low	Very High
Patient PX-14...	000	Low	High
Patient PX-15...	000	Medium	High

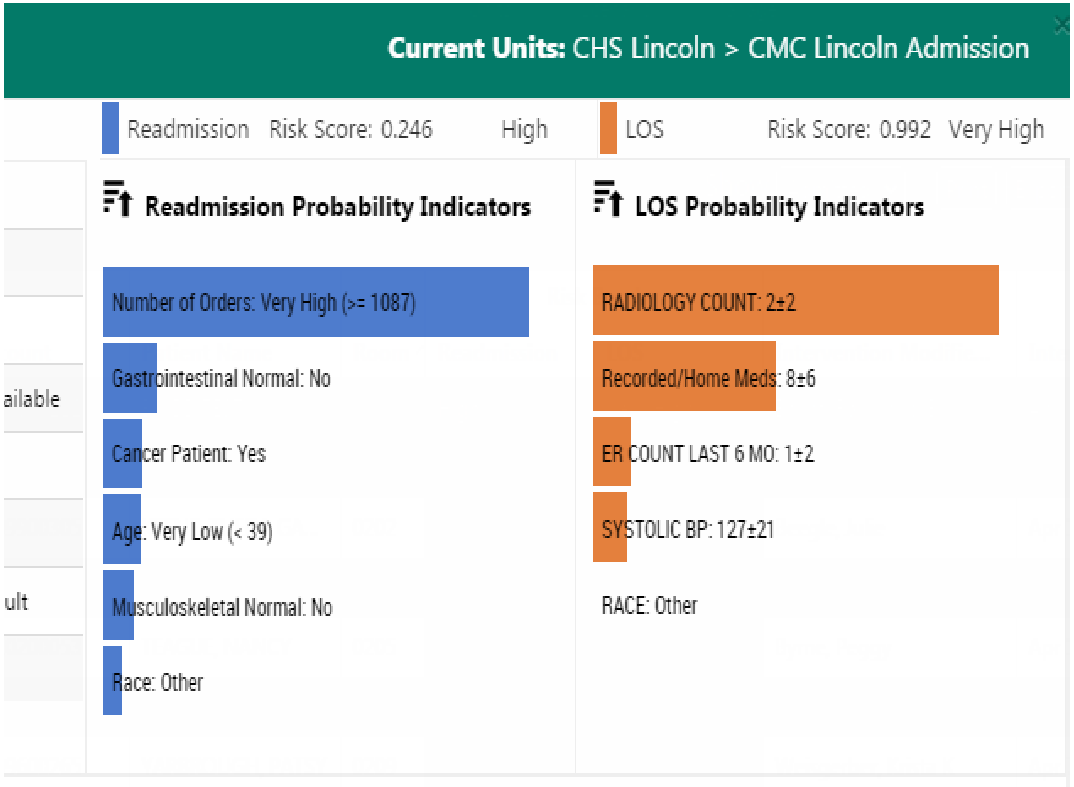
Where are they located?

What is driving their risk?



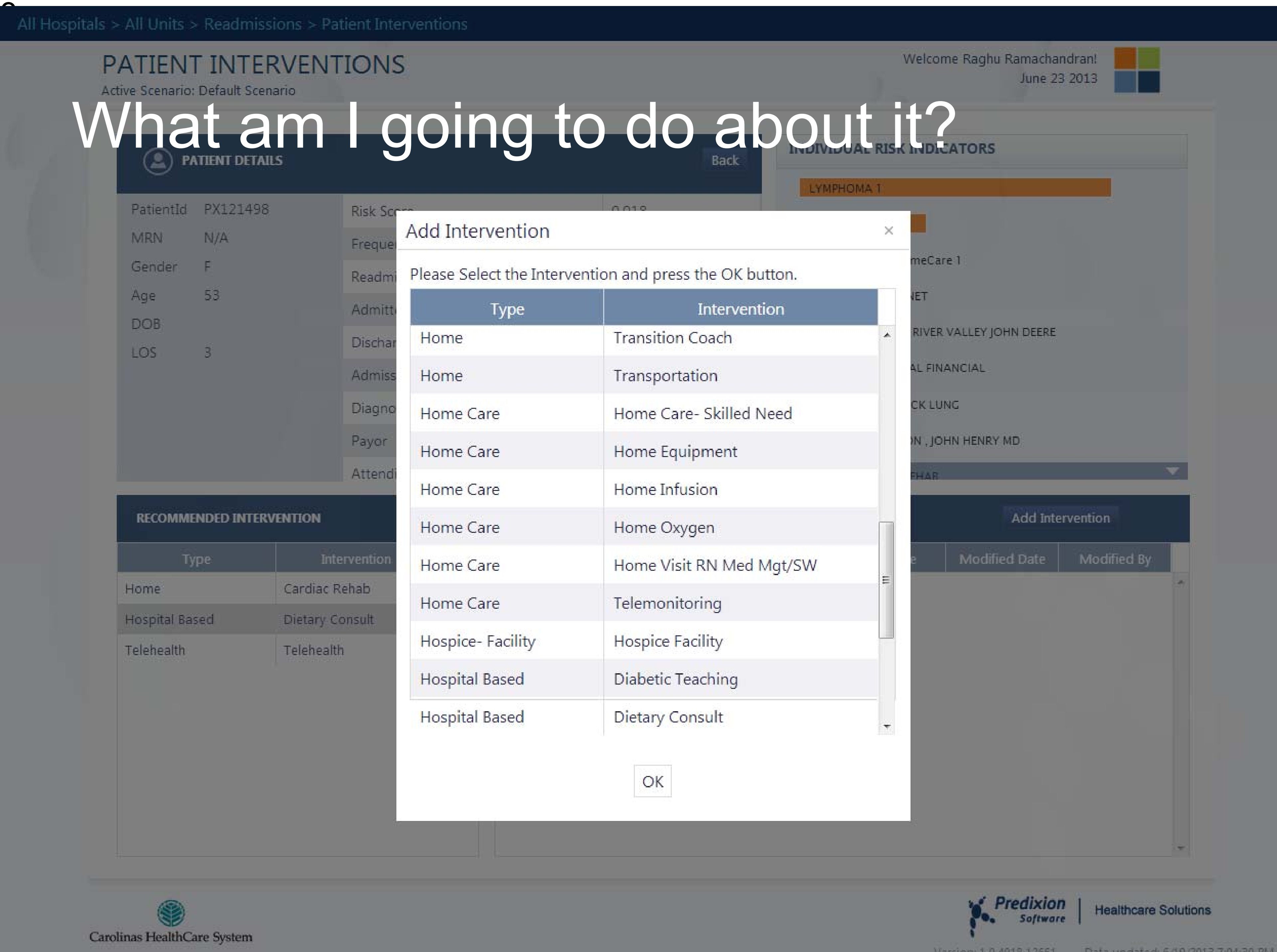
Individual Patient View

What is driving the risk?



Intervention lifecycle and tracking

What am I going to do about it?



Patient Risk Assessment

Then		Now
Done After EMR and Patient Review Care managers need to review the patient's chart and examine the patient prior to assessing risk	→	**Done Prior to Seeing Patient** Allows care managers to work more effectively by prioritizing their workflow and more efficiently through automating the risk assessment.
Limited Capability Care managers assign risk based on a a few simple criteria that group patients into two buckets: low risk and high risk	→	**Risk Assessed from Predictive Model** Patient risk for readmission is predicted, automatically, from over 40 key variables pulled from Cerner
Case Manager Variation Care manager ability to find and assess risk factors varies	→	**Automation Decreases Variation** Patient risk is automatically calculated for the care managers
Done at Admission Care managers only have capacity to assess patient risk at admission	→	**Updated Hourly** A patient's condition and likelihood for readmission can change throughout a hospital stay; our tool captures these changes hourly as clinical data change

Care Interventions

Then

Difficult to Hardwire
Care managers required to recognize a certain patient type and remember what interventions are to be assigned to the patient

Difficult to Measure Interventions
Current care management tools do not allow for evaluation of intervention efficacy; limits our ability to leverage our System

Now

Recommendations Assigned Automatically
Patients automatically assigned interventions based on their personal characteristics

Measure Efficacy Interventions
Capture of interventions and data around outcomes will allow us to measure the efficacy of interventions and determine patients who optimally benefit

Additional Benefits

- Potential to improved the productivity of nurses and case managers
  - Instead of basing rounds on room number, time of discharge or other information, a reliable method of working the list of patients can be developed.
  - Case Managers can now be deployed based upon the complexity of the patients and their likelihood of readmission
- Ability to better predict work loads across floors and units
- Risk stratification for Transition of Care calls
- Communication of risk to post acute care providers

Triage of Risk for Transitional Care

VERY HIGH RISK

HIGH RISK

Telehealth Call Center
Transitional Care Call

VERY HIGH RISK

HIGH RISK

Transitional Care Clinic

Time to Deploy Models

- Our 3 year experience in building and deploying models now shortens the adoption curve for every organization that follow in our path.

- A recent deployment in rural North Carolina, took only 5 days to get the model validated, the Case Managers trained, and the model into their hands.

- By Friday, cases were being managed differently.

Potential to deploy visualization across devices

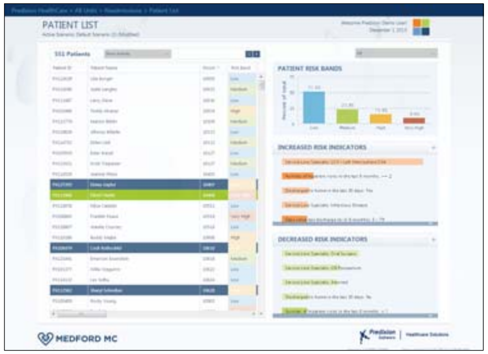
Portable Web Applications

Interactive Mobile Apps

Dashboard Integration

Embedded CRM

Embedded IoT

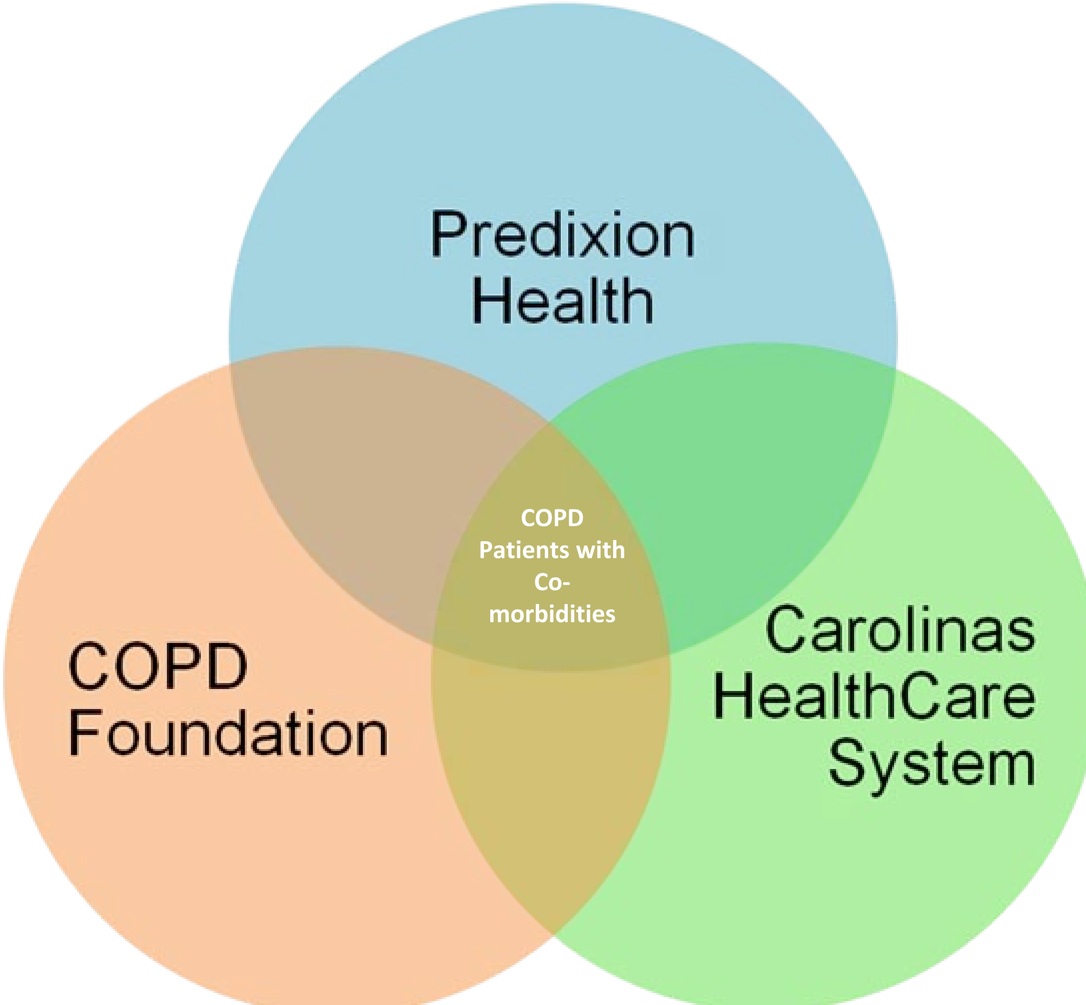


Solution Accelerator

Improving care for patients with COPD by using predictive analytics at the point of care

A collaboratory between the COPD Foundation,
Carolinas HealthCare System,
Predixion Software, and Glaxo Smith Kline

Patient-Centered, Point of Care COPD Learning Collaboratory



Academics

Clinical Leaders

Board members

Industry

Key Predictors of Readmission Risk

Demographics

Age
Race Code
Insurance
Hospital Name
Service Provided
Admission Type
Transf

Co-morbidities

Primary Diagnosis
Any Malignancy
Cerebrovascular Disease
Charlson Comorbidity Score
Chronic Pulmonary Disease
>9 Meds and >9 Problems
End Stage Renal Disease

Built from our experience with Readmission 1.0 & 2.0

Psychosocial

Clinical Nutrition Consult
Living Situation
Need Transportation Assistance
Physical Therapy Consult

Utilization

Days since last discharge (w/in 6 months)
Number of Inpatient visits in the last 6 months
Number of ED visits in the last 6 months
Number of Transfers
Discharged to home in the last 30 days

Continued…

Key Predictors of Readmission Risk

Labs/Vitals/Meds

Recorded/Home Meds
Meds in the last 24 Hrs
Albumin Level
Ammonia level
Arterial Lactate
Blood Transfusion

Fall Risk Score
Gastrointestinal Normal
Glomerular Filtration Rate
Feeding Tube
Hemoglobin
HGB A1C
Inability to Verbalize Needs
Musculoskeletal Normal
Neurological Normal
Nutrition Braden Score

O2 saturation
Proton Pump Inhibitor
Orientation
Oxygen Flow Rate
Oxygen Improved Status
Oxygen Therapy Type

Safety and Judgment
Scooting
Sit to Stand
Sit to Supine
Skin Description
Systolic BP
Toilet Use Mobility
Tracheal Post Treatment
Venous Lactate

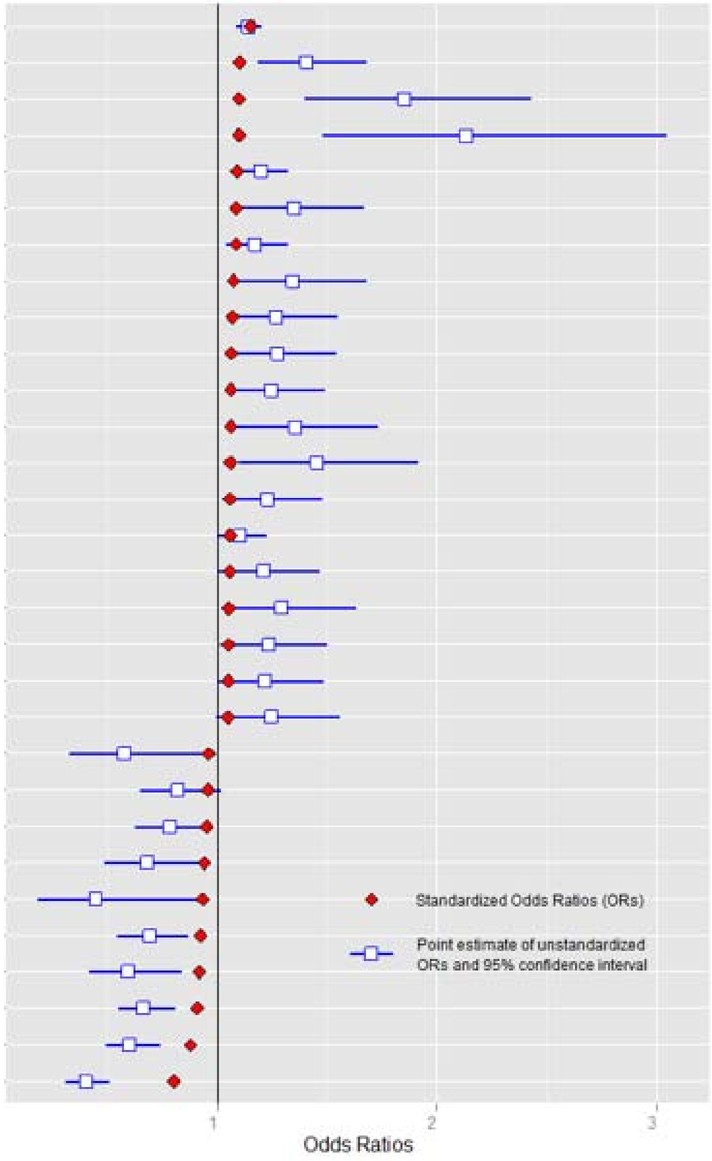
Built from the literature and experts in COPD care

COPD Readmission Risk Model

Built on nearly 8000 discharges with a CMS defined COPD or Asthma Diagnosis


KitchenAid
KitchenAid
KitchenAid

Actionable insights by comparing odds ratios

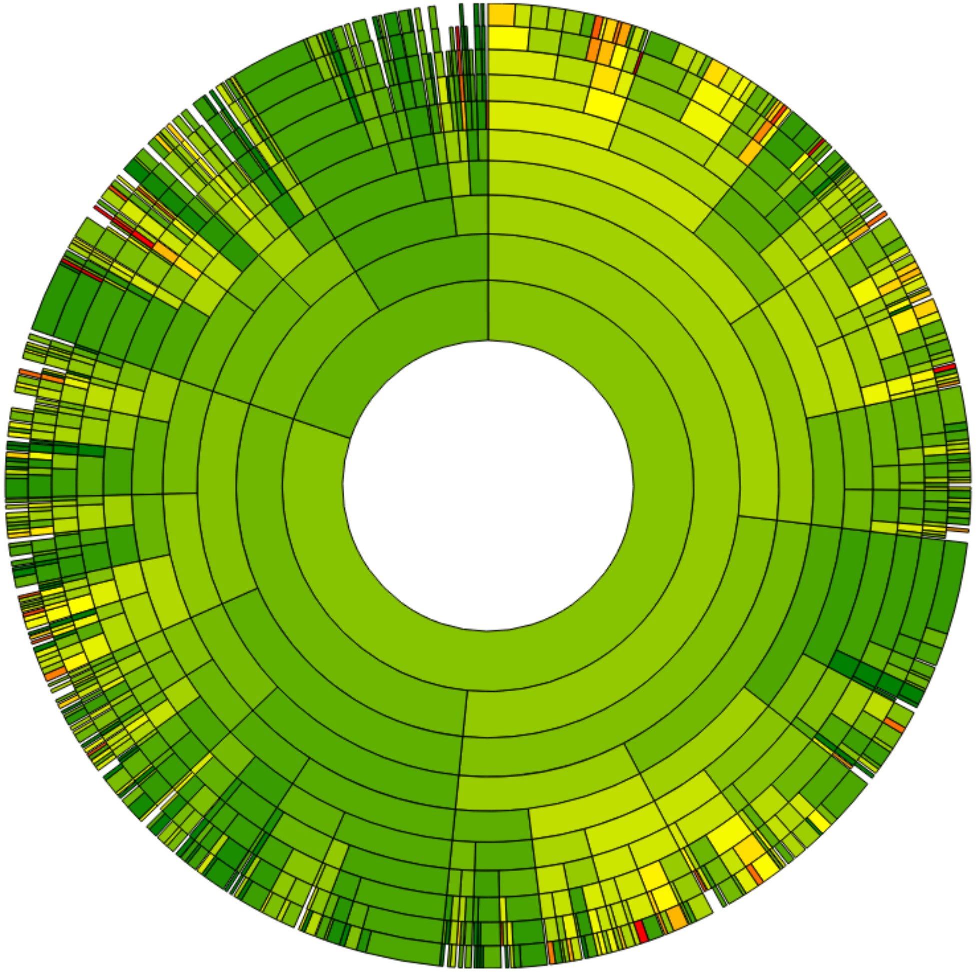


CHF Combination of Conditions

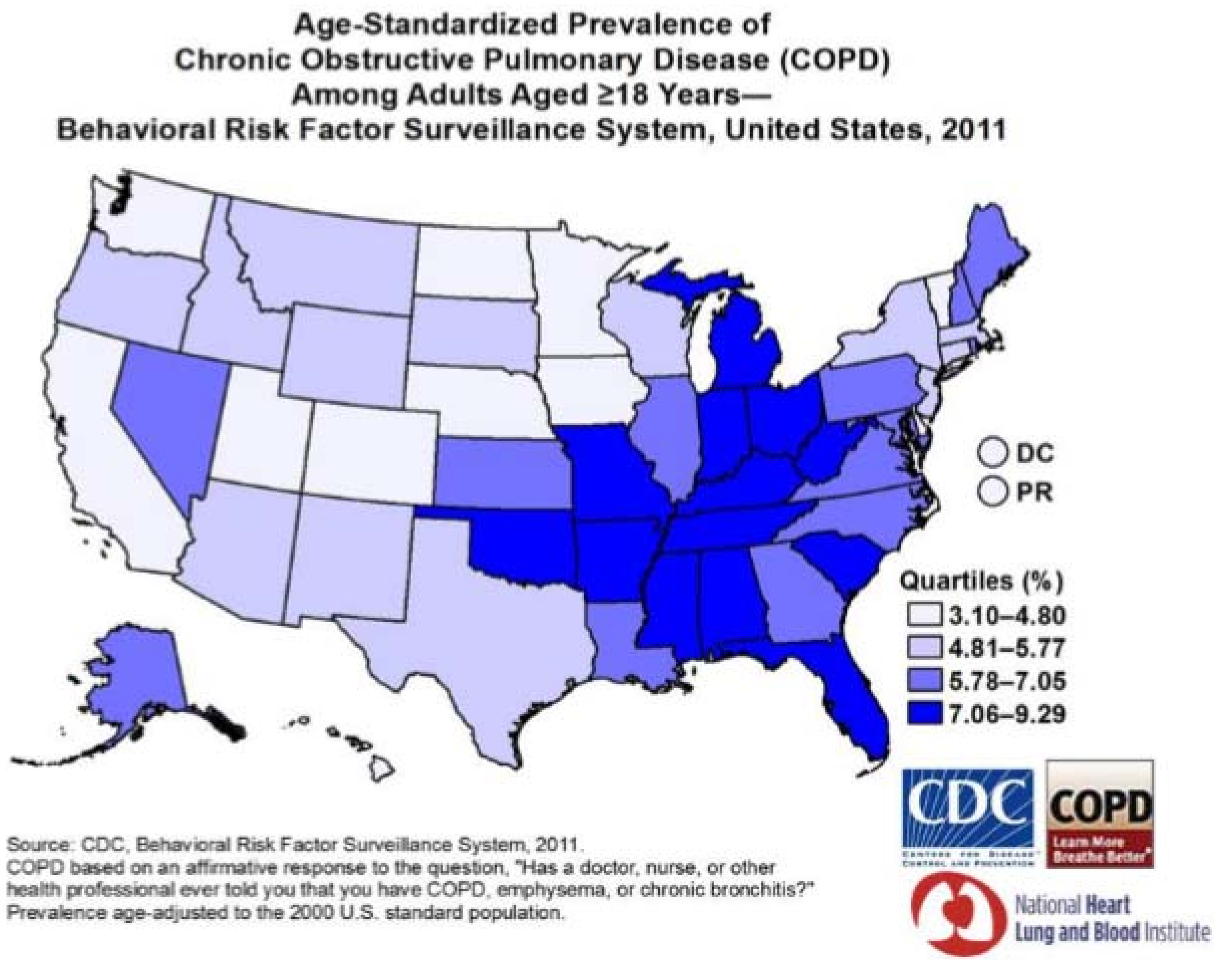
Severity of Top 20 combinations (accounts for 75% of COPD+CHF patients)

Comorbidity combination	Count	Proportion	Readmission Rate	Label
10010001	55	1.9%	12.7%	CHF + OP + Anxiety
10001001	97	3.4%	12.4%	CHF + OA + Anxiety
11000000	228	7.9%	14.0%	CHF+ HTNDis
10000000	372	12.9%	15.9%	CHF only
10001000	81	2.8%	16.0%	CHF + OA
10000001	221	7.6%	18.1%	CHF + Anxiety
10000100	138	4.8%	18.1%	CHF + DM
10001100	38	1.3%	18.4%	CHF + OA + DM
11100100	38	1.3%	18.4%	CHF + HTNDis + Anemia + DM
11001101	69	2.4%	18.8%	CHF + HTNDis + OA +DM +Anxiety
11001100	57	2.0%	19.3%	CHF + HTNDis + OA +DM
11000001	85	2.9%	20.0%	CHF + HTNDis + Anxiety
10011001	41	1.4%	22.0%	CHF + OP + OA + Anxiety
10000101	125	4.3%	24.8%	CHF + DM + Anxiety
10001101	71	2.5%	26.8%	CHF + OA + DM + Anxiety
11000100	160	5.5%	27.5%	CHF + HTNDis + DM
11001001	74	2.6%	28.4%	CHF + HTNDis + OA + Anxiety
11100101	37	1.3%	29.7%	CHF + HTNDis + Anemia + DM +Anxiety
11001000	63	2.2%	33.3%	CHF + HTNDis + OA
11000101	108	3.7%	35.2%	CHF + HTNDis + DM + Anxiety

Visualize the Relationships of COPD with Comorbidities

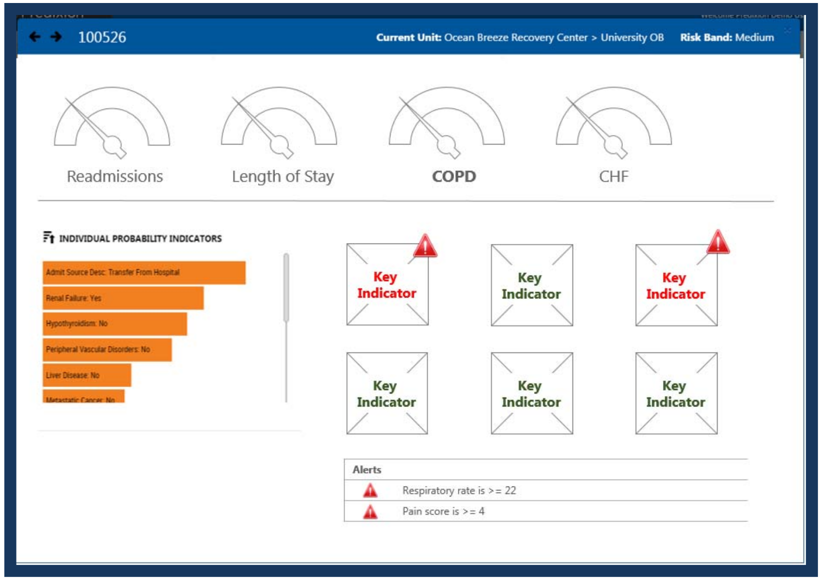


COPD prevalence varies across the country



Insights from our recent Design Session for Predictive Personalized Medicine Interface

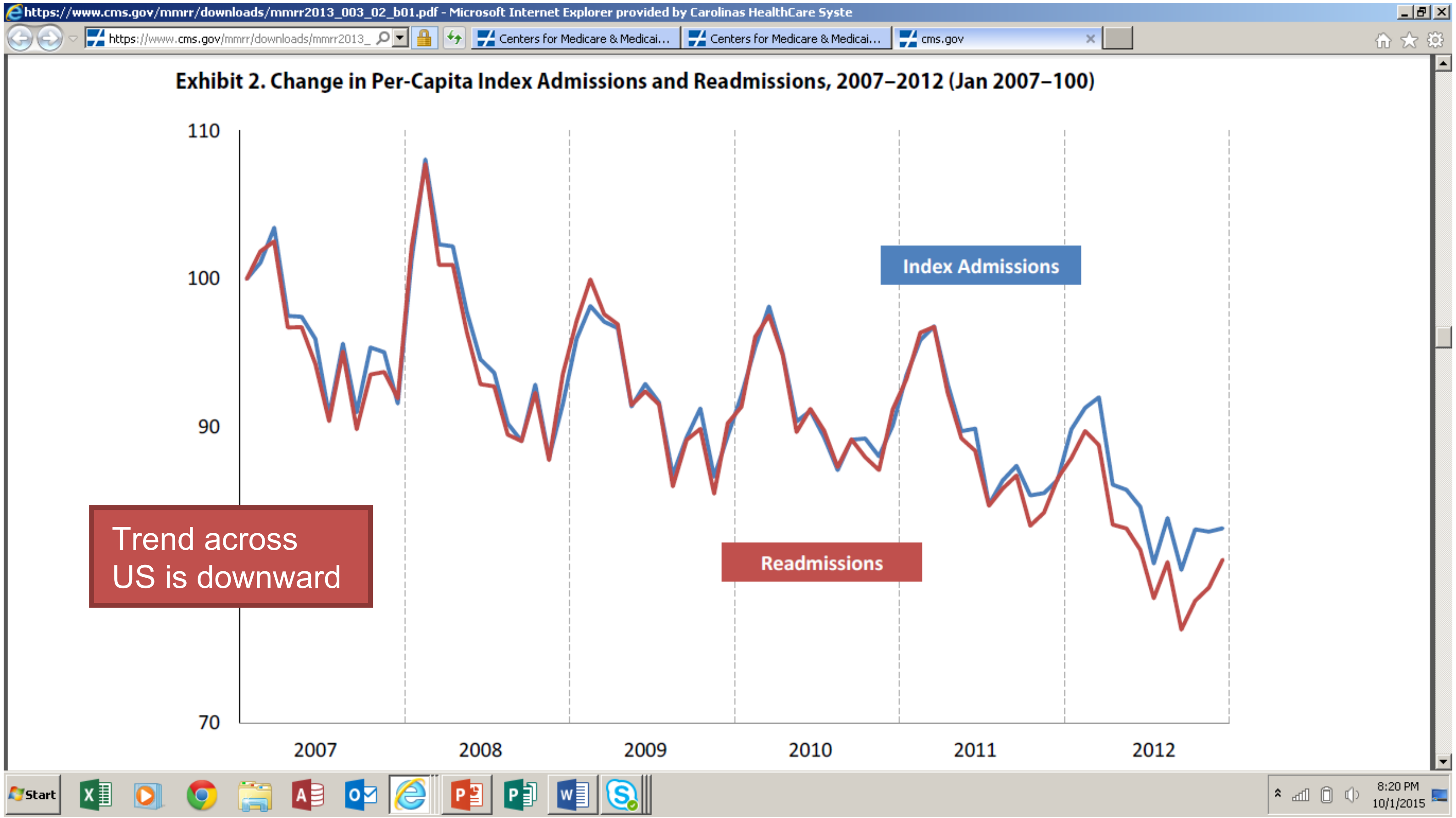
Involved end-users for designing the interface
- Case Managers
- Hospitalists
- Primary Care Physicians
- Pulmonologists
- Respiratory Therapists
- Pulm Rehab Team



Video Re-enactment

- http://sendvid.com/5kq3a1l5?secret=653da4fa-450d-4af9-af36-b924614d39e8

Trend across the country is down

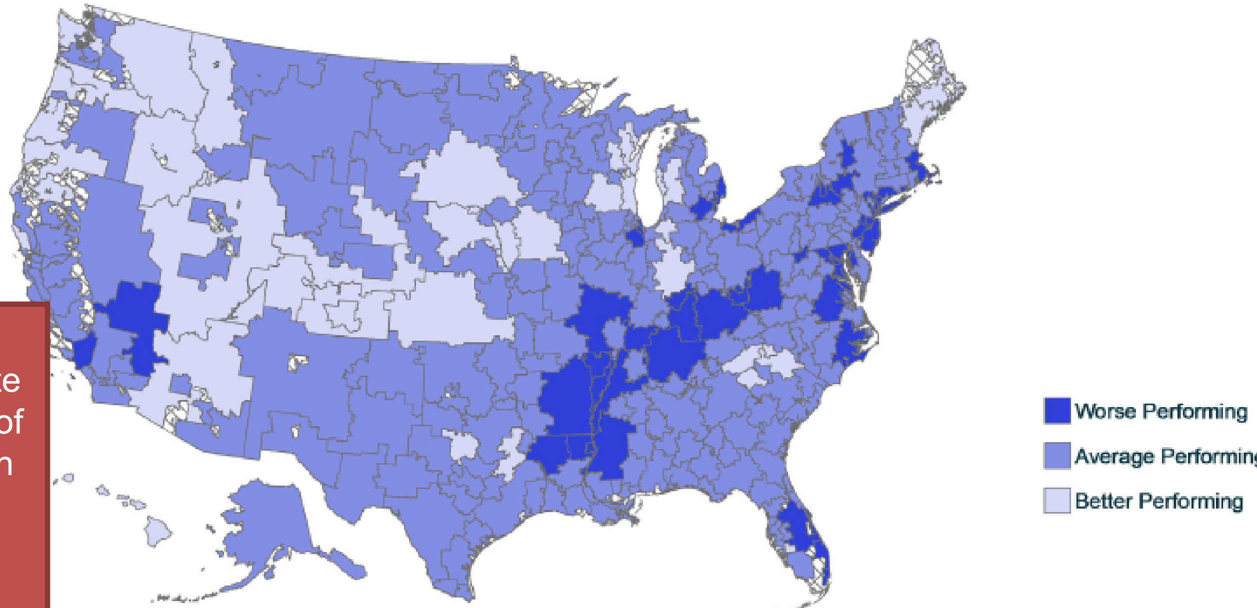


HOSPITAL-WIDE | READMISSION

GEOGRAPHIC VARIATION

▶ Does overall performance on the hospital-wide unplanned readmission measure differ by geographic location?

FIGURE I.C.4. *Classification of hospital referral regions (HRRs) by RSRR for hospital-wide readmission, July 2012 – June 2013.*



Trend across US is downward and Charlotte has outperformed rest of country (and better than this same graph previous year).

What does improving your O/E mean?

- Using just a percentage doesn't reflect the case mix of your organization.
  - The Cardiothoracic program was moved from one hospital to another. The Case Mix radically changed at both.
- Using a percentage doesn't reflect the changes in care, and how they impact subsequent admissions and readmissions
  - As you get better at readmissions, you get better at Admissions, and the patient population changes in your hospital
- As your O/E improves, you demonstrate that your organization is pulling away from similar hospitals with similar patients.

Improving Observed to Expected Ratios

Hypothethical Hospital	10,000 discharges a year
Number of readmissions **expected**	1800 readmissions a year
Number of readmissions **observed**	1800 readmissions a year

If the number of readmissions = the number expected: 0/E = 1

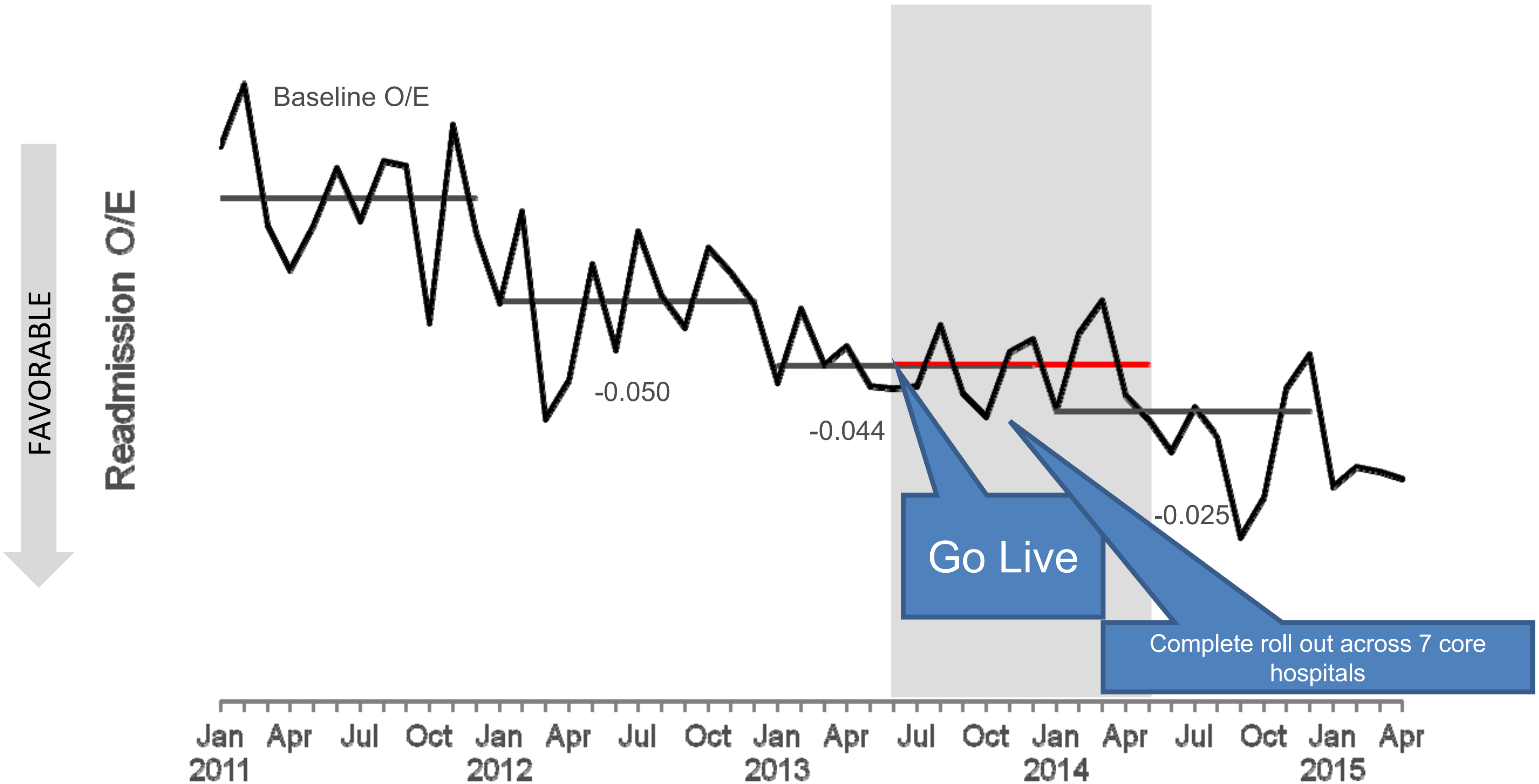
If the number of readmissions is reduced 10%,

Number of readmissions expected is	1800 readmissions a year
Number of readmissions observed is	1680 readmissions a year

Then the O/E ration goes to 1680/1800 or 0.93

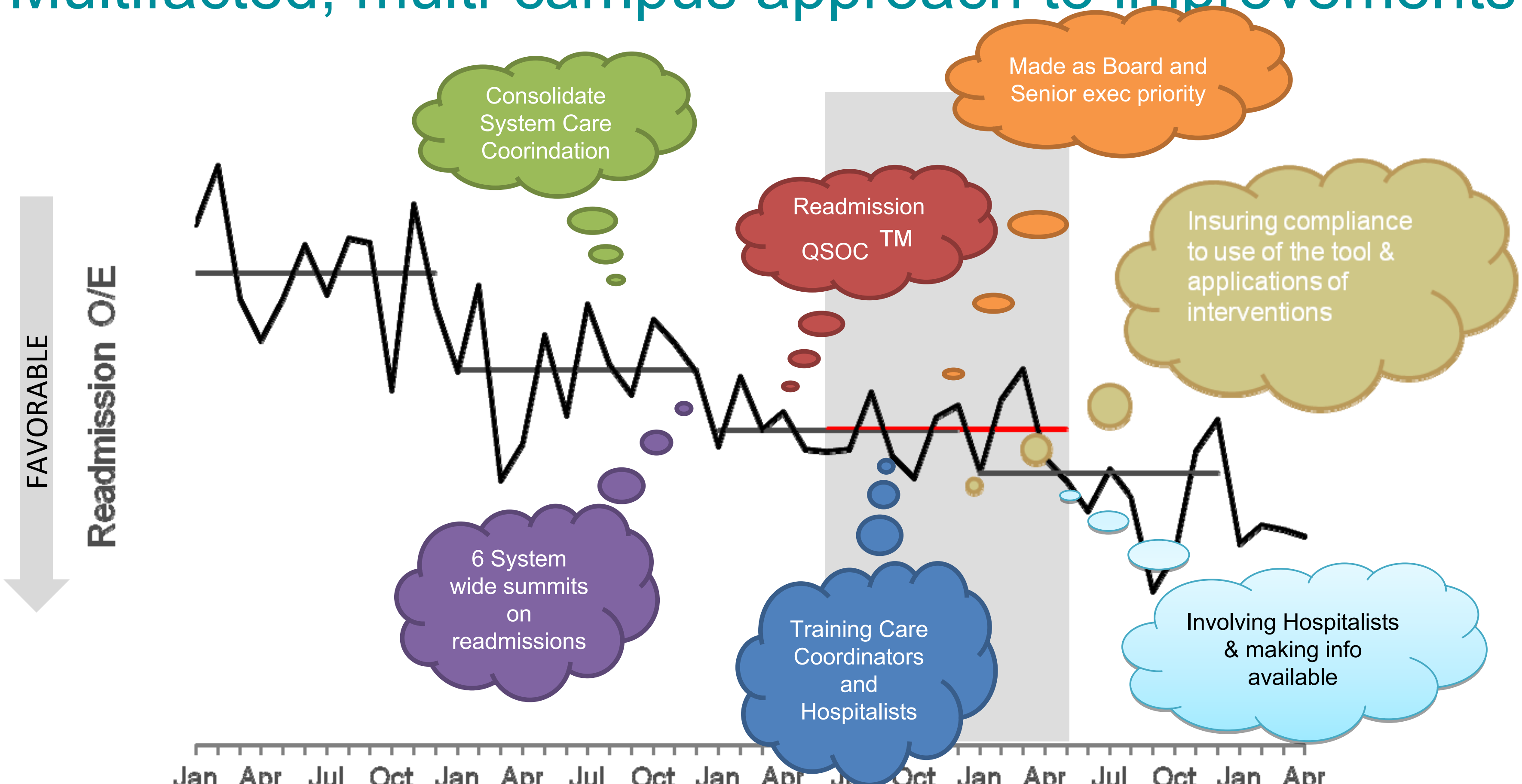
As O/E is less than 1.0, there is a continued improvement in performance.

Carolinas HealthCare System Readmissions Journey
Implementation of Predixion™



*Updated 7/14/2015

Carolinas HealthCare System Readmissions Journey
Multifacted, multi-campus approach to improvements



*Updated 7/14/2015

Results

- In the metro city Charlotte market, CHS recently saw an even further drop in readmissions by requiring the use of a standard order set amongst hospitalists caring for patients with COPD.

- Coupling standardized management with interventions aimed at the highest risk populations dropped the readmission rate in half again.

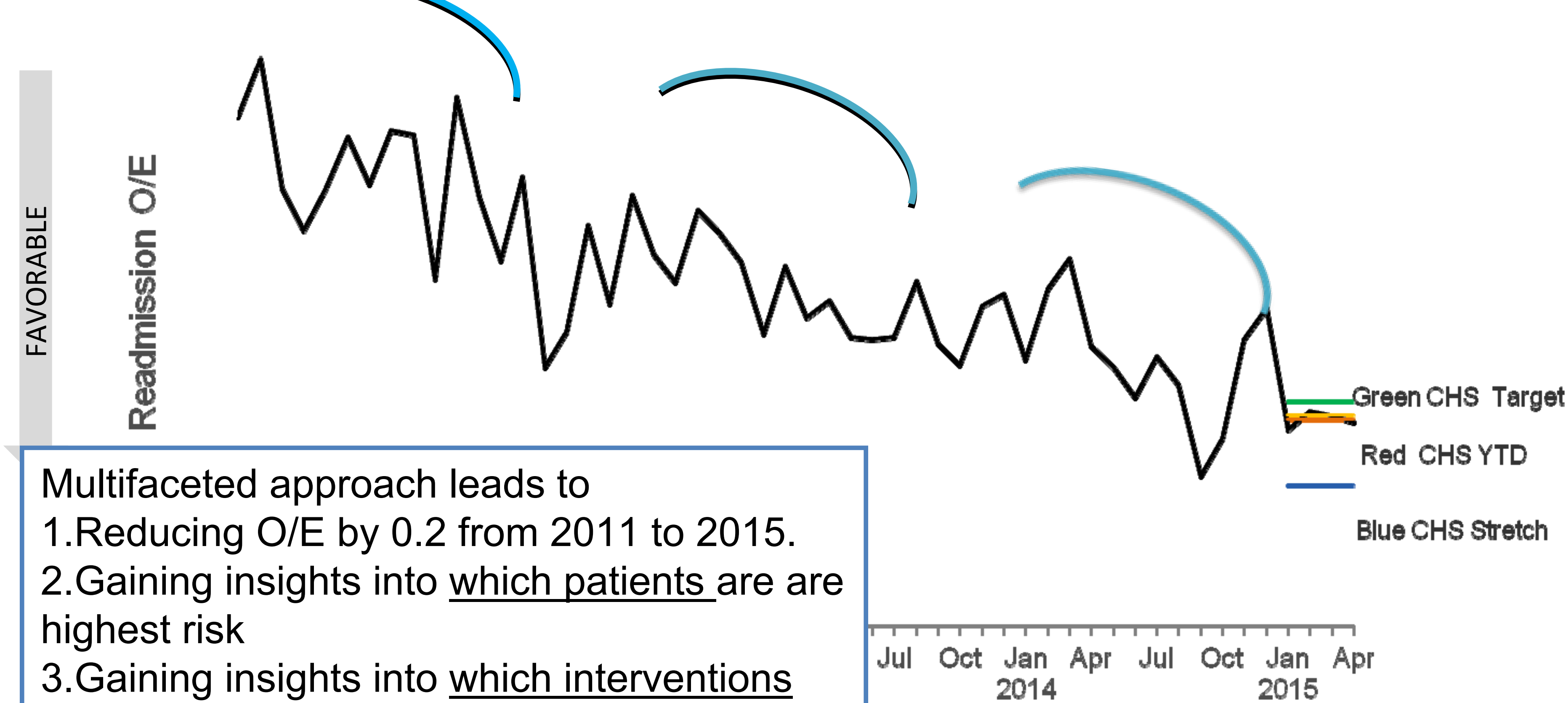
- So what does this tell us? A sharper focus built upon predictive analytics, coupled with intentional strategies aimed at the highest risk patients, can measurably decrease the readmission rate.

CHS Multi-year Journey on Readmissions

- Consolidated Case Management Across Metro Hospitals
- System wide Summits held on the topic of readmissions
- A CHS QSOC ™ was formed and meets quarterly
- A System Wide Executive Steering Committee was formed.
- Although CMS was focusing penalties on only 3 DRG at the inception of the program, CHS chose to internally measure it's performance against all diagnoses, and all causes.
- Co-development of model of readmissions based upon 2 years of historical data from CHS (> 300K discharges).
- Training of Case Management in use of Predixion Tool
- Development of accountability of Case Managers for using tool and applying appropriate interventions.
- Spread of use of tool beyond just Case Management
- Importance of readmissions reflected in its outcome linked to Executive Dashboard.
- You must have an accurate focus on the impactable patient, and apply the meaningful interventions.

Carolinas HealthCare System Readmissions Journey
Rolling Waves of Improvement

So what does this mean?



Multifaceted approach leads to
1. Reducing O/E by 0.2 from 2011 to 2015.
2. Gaining insights into <u>which patients</u> are are highest risk
3. Gaining insights into <u>which interventions</u> impact readmissions.

Conclusion

- Carolinas HealthCare System (CHS) has been on a multi-year journey to meaningfully decrease unplanned 30 day readmissions.
- Since adopting predictive analytics as part of their comprehensive strategy in summer of 2013, CHS has managed over 300,000 patient discharges in the hands of 200 case managers.
- As part of a comprehensive strategy, CHS has seen year over year improvement in decreasing the readmission O/E, and has increased insight into which patients should receive transition of care services.
- It's all about change management


Be the
Change