#FSHP2018

FSHP

Predictive Analytics

A Focused Approach to Improving Outcomes

Peter Duggan, RPh
Gulf Coast Medical Center, Ft Myers

Break Through Branch Out

Disclosure

I do not (nor does any member of my immediate family) have a vested interest in or affiliation with any corporate organization offering financial support or grant monies for this continuing education activity, or any affiliation with an organization whose philosophy could potentially bias my presentation.

Break Through #FSHP2018 Branch Out

Objectives

- Describe reasons patient risk stratification functionality is important for hospital pharmacy teams.
- Discuss challenges or barriers with implementation of risk stratification tools in a hospital EHR.
- Describe examples of patient risk stratification that have been implemented in a hospital pharmacy department.

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A Brief History

Edward Lloyd's Coffee House

1689 – Lloyd's coffee house is established in London to deliver reliable shipping news to interested parties

Bankers would accept risk for a given voyage in exchange for a premium by writing their names under the risk information derived from the shipping news

http://canworksmart.com/history-of-predictive-analytics/

Break Through #FSHP2018 Branch Out

A Brief History

20th Century

www.fico.com/analytics

Break Through #FSHP2018 Branch Out

Rationale

Industry use of predictive analytics:

- Casinos – careful modelling of customer flow and payouts
- Travel – when where and how people will travel
- Energy – predicting hour-by-hour energy usage ensures capacity meets demands
- Agriculture – razor thin margins make predictions of crop prices, weather, pesticide use and livestock feed costs critical
- Mining – long term security can be dependent on predicting global demand for raw materials

www.fico.com/analytics

Break Through #FSHP2018 Branch Out

Rationale

Healthcare

- Increase the accuracy of diagnosis
- Improve preventive medicine and public (population) health
- Improve individualized treatments
- Improve cost projections
- Allows researchers to develop better prediction models
- Improve patient outcomes

Winters-Miner L. *Practical Predictive Analytics and Decisioning Systems for Medicine.* Elsevier 2012

Rationale

$ 750 Billion

"According to the National Academy of Medicine (formerly the Institute of Medicine), the U.S. healthcare system spends almost a third of its resources on unnecessary services and inefficient care."

12%

Percentage of U.S. population with 5 or more chronic conditions that consumes > 40% of healthcare expenditure

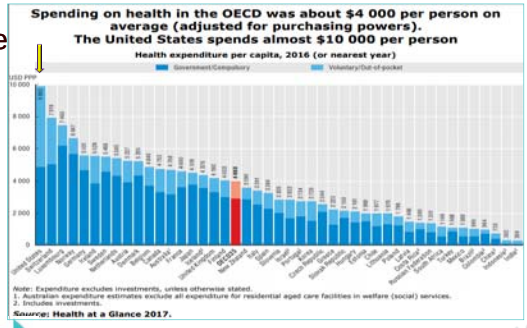
5.5%

CMS projected annual increase in healthcare expenditure for the next decade.

Kalad et al. Getting Buy-in for Predictive Analytics in Healthcare. HBR June 2017

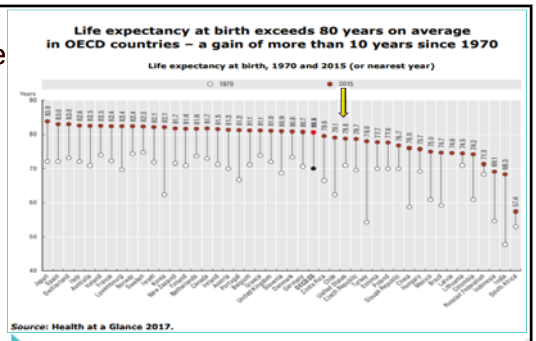
Rationale

The best healthcare money can buy?



Rationale

Life expectancy below the OECD median.



Challenges and Barriers

"It's tough to make predictions, especially about the future."

- Yogi Berra

Challenges and Barriers – System Selection

Targeted Utility

It is difficult to extract clinically relevant conclusions from a large database. It is important to select variables that contribute to and stand out from background noise when attempting to assign risk for a particular clinical condition to a specific patient.

Data Feeds

The power of predictive analytics lies in the ability to apply algorithms to multiple, possibly unrelated or not readily accessible data feeds that even a careful human observer may not be able to accurately interpret. Success is dependent on obtaining all the necessary data.

Crockett D. Four Essential Lessons for Adopting Predictive Analytics in Healthcare. Health Catalyst 2013

Challenges and Barriers – System Selection

Trust

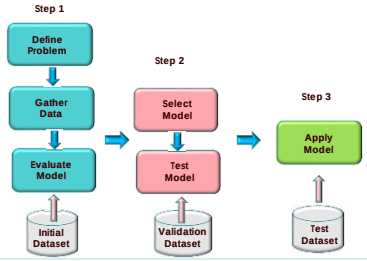
Adoption by clinicians is based on trust in the model. Final outcomes data must be captured during testing to validate accuracy. This validation may result in extended lead times to implementation.

The challenge of implementation

Many options exist, including open-source software. It's important to partner with groups that have a thorough understanding of academic and commercial tools as well as the expertise to develop a model that fulfills your organizational needs.

Crockett D. Four Essential Lessons for Adopting Predictive Analytics in Healthcare. Health Catalyst 2013

Challenges and Barriers – System Selection



Overview of machine learning

Crockett D. Four Essential Lessons for Adopting Predictive Analytics in Healthcare. Health Catalyst 2013

Challenges and Barriers – System Selection

www.wired.com/story/a-robot-does-the-impossible-assembling-an-ikea-chair-without-having-a-meltdown/

Challenges and Barriers – Selling the Concept

Engage the Right People

Whether home grown or "off the shelf"- these tools require extensive validation and ongoing improvement. A multi-disciplinary team all of whom possess behavior change skill sets should minimally include:

- Clinicians
- Finance
- IT

A **defined problem** that can be improved through the application of predictive analytics and has clear value for the organization should be selected.

Kalad et al. Getting Buy-in for Predictive Analytics in Healthcare. HBR June 2017

Challenges and Barriers – Selling the Concept

Change Agents and Clinical Champions

Well respected clinicians and other thought leaders when partnered with implementation experts are often essential to success.

These clinical champions should actively promote the tool, map workflows, identify needed changes, and educate end users on the expected benefits.

These leaders will generate and maintain the momentum needed to bring the project to completion.

Kalad et al. Getting Buy-in for Predictive Analytics in Healthcare. HBR June 2017

Challenges and Barriers – Selling the Concept

The C-Suite

Engagement at the highest levels of organizational leadership, especially the CEO, is as important as clinician leaders and front line staff.

Models can de-calibrate and require maintenance. Long-term sustainability of these tools can be supported by the development of a compelling scorecard – an executive dashboard that quantifies the value of the tool can serve to educate senior leadership on its utility.

To fully realize the benefits of these tools, a thoughtful approach must be taken to making them a seamless part of user workflow. Committed leadership and a resulting culture that is supportive of change and integral to success.

Kalad et al. Getting Buy-in for Predictive Analytics in Healthcare. HBR June 2017

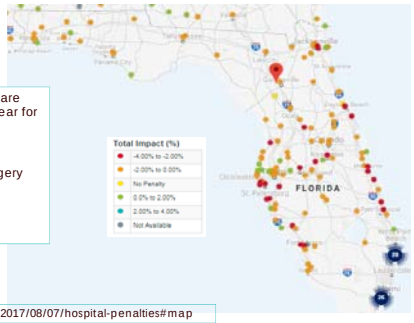
Risk Stratification

Selecting a defined problem

Problem

Over 2500 hospitals will face Medicare readmission penalties of 1-3% this year for the following conditions:

- Chronic lung disease
- Coronary artery bypass graft surgery
- Heart attacks
- Heart Failure
- Hip and Knee replacements
- Pneumonia



https://www.advisory.com/daily-briefing/2017/08/07/hospital-penalties#map

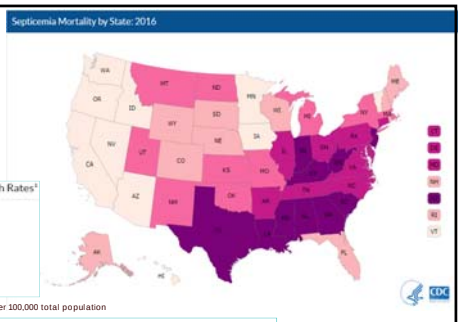
Problem

Sepsis:

1.5 million cases per year

250,00 deaths annually

One on three hospital deaths



[1]The number of deaths per 100,000 total population

https://www.cdc.gov/nchs/pressroom/sosmap/septicemia_mortality/septicemia.htm

Risk of Unplanned Readmission

Model Brief

Reduced reimbursement for Medicare patients readmitted within 30 days has resulted in the development of programs such as BOOST (Better Outcomes by Optimizing Safe Transitions) and RED (Re-engineered Discharge) to reduce unplanned readmissions.

Resource constraints at many hospitals result in too few patients being screened for targeted interventions

Identifying patients with risk factors that contribute to higher probability of readmission allows strategic allocation of limited resources

Risk of Unplanned Readmission

Model Brief (continued)

Machine learning based on:

- 3 years of data from the EPIC community
- > 275,000 hospital admissions
- > 200,000 unique patient records
- > 200 variables evaluated final model built using
  - Diagnosis (Elixhauser Comorbidity, Charlson Comorbidity Index)
  - Current Age
  - Lab values – 72 hr. look-back (Hgb, Ca, INR, Phos, BUN, Creatinine)
  - Medications - # meds, steroids, coag, anti-psych, NSAIDS, PPIs & H2RAs)
  - Order Types – EKG, imaging, restraints
  - Utilization – LOS, Past ED Visits, Future appts, past admits, prev LOS > 10 days

Risk of Unplanned Readmission

Validation

Initial validation conducted beginning Fall 2017 – 7100 encounters used

No population exclusions

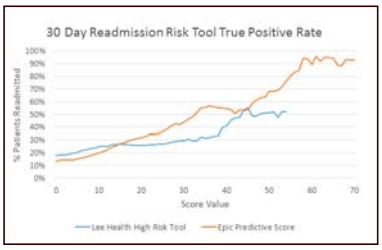
C-Stat scores:

- Predictive Score: 0.71
- LACE+: 0.63-0.69
- High Risk Score: 0.64

Risk of Unplanned Readmission

Comparison of true positives

- Existing tool predicted 50% of readmissions at highest score
- New Predictive tool predicted **95%** of readmissions at highest score



Risk of Unplanned Readmission

Risk of Unplanned Readmission

- Refreshes every 4 hours
- Hover to find contributing factors
- Uses 27 categories and many more sub-categories for risk stratification.

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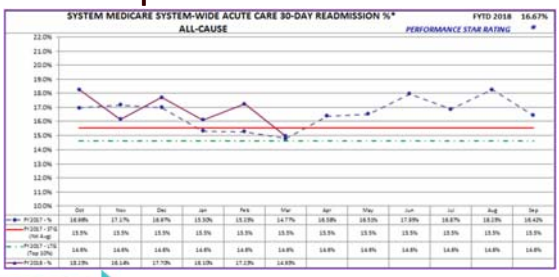
Risk of Unplanned Readmission



Sepsis

Model Brief

Quick progression and high mortality rate makes early diagnosis and rapid intervention crucial to saving lives .

An accurate predictive model that is fully integrated into clinician workflows can give early warning for a rapid response

Such a model must be sensitive enough not to miss patients, but accurate enough to avoid large numbers of false positives.

Sepsis

Model Brief (continued)

Machine learning based on:

- 3 years of data from the EPIC Community
- Over 500,000 patient encounters
- > 350 variables analyzed, final model built using:
  - Demographics
  - Vitals
  - Recent lab results
  - Medications
  - Comorbidities
  - Active lines, drains, and airways

Sepsis

National Early Warning Score (NEWS)
Developed in the UK as a risk stratification tool for patients at risk for any critical illness.

Not specific to sepsis, but it combines elements of SIRS and qSOFA so may be more sensitive than either alone

Components of SIRS, qSOFA, MEWS, and NEWS

	SIRS	qSOFA	MEWS	NEWS
Temperature	✓		✓	✓
Heart rate	✓		✓	✓
Blood pressure		✓	✓	✓
Respiratory rate	✓	✓	✓	✓
Oxygen saturation				✓
Use of supplemental oxygen				✓
Mental status		✓	✓	✓
Leukocyte count	✓			
Urine Output			✓	

Sepsis

National Early Warning Score (NEWS)*

PHYSIOLOGICAL PARAMETERS	3	2	1	0	1	2	3
Respiration Rate	≤8		9 - 11	12 - 20		21 - 24	≥25
Oxygen Saturations	≤91	92 - 93	94 - 95	≥96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤35.0		35.1 - 36.0	36.1 - 38.0	38.1 - 39.0	≥39.1	
Systolic BP	≤90	91 - 100	101 - 110	111 - 219			≥220
Heart Rate	≤40		41 - 50	51 - 90	91 - 110	111 - 130	≥131
Level of Consciousness				A			V, P, or U

*The NEWS initiative flowed from the Royal College of Physicians' NEWS Development and Implementation Group (NEWSDIG) report, and was jointly developed and funded in collaboration with the Royal College of Physicians, Royal College of Nursing, National Outreach Forum and NHS Training for Innovation
© Royal College of Physicians 2012

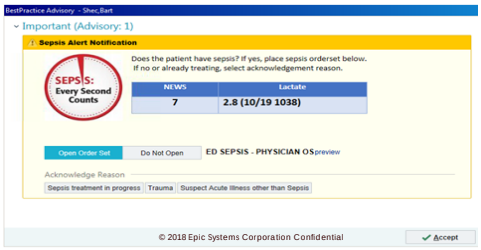
Sepsis

NEWS Score

- Not calculated for patients < 18
- NEWS score column added to ED tracker
- Patient header displays NEWS score
- "Sepsis Risk" Indicator displays in the patient header for NEWS 5 or >
- In the ED:
  - ➢ NEWS score 5 or greater fires a sepsis risk alert for Nurses
  - ➢ NEWS score 5 or greater **+** lactate 2 or greater **<u>or</u>** NEWS 7 or greater fires sepsis alert for Physicians and Mid-Levels
- Inpatient:
  - ➢ Critical Care Outreach RN alerted for NEWS 7 or greater

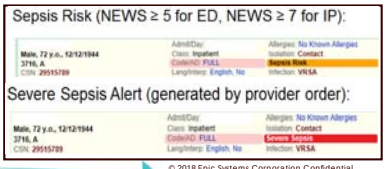
Sepsis

➢ NEWS score 5 or greater **+** lactate 2 or greater **<u>or</u>** NEWS 7 or greater fires sepsis alert for Physicians and Mid-Levels



Sepsis

NEWS score appears in the ED tracker



Sepsis Risk based on NEWS score appears on the inpatient header.

Sepsis

Sidebar Checklist

- Activated by the Sepsis Alert Order
- Contains banners for required items that have not been completed
- Banners are removed as items are completed

Sepsis

Vasopressor Alert

- Appears after 2 consecutive BPs meet criteria (SBP <90 or MAP <65)
- Selection of vasopressors offered for ICU patients
- Critical Care consult offered for MedSurg/PCU patients

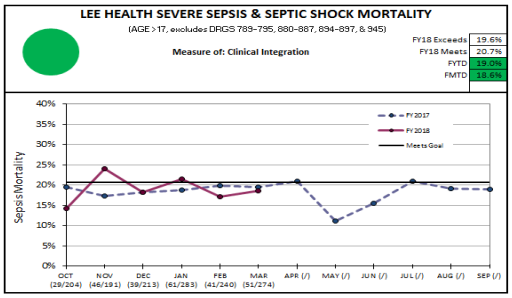
Sepsis

Six hour Sepsis Note

- Appears 4 hours after severe sepsis order has been placed.

Sepsis

2016 mortality rate for hospitalized patients with sepsis is **26%**



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References

Open source analytics:

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The Waikato Environment for Knowledge Analysis (WEKA): http//:www.cs.waikato.ac.nz/ml/weka

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OECD Data : https://data.oecd.org/

CDC Data : www.cdc.gov/datastatistics/index.html

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