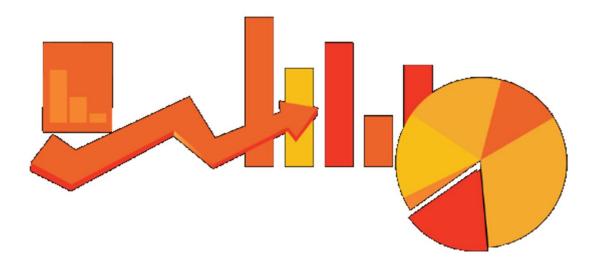
# Analytics Track AMDIS 2014

Moderated by Christopher Longhurst, MD, MS

VP of Analytics and Informatics

Stanford Children's Health



#### True North at Stanford Children's



# Enable effective and efficient decision making through user-friendly access to quality information.





Lucile Packard
Children's Hospital
Stanford

# The Gamut of Analytics

- Population health management Dick Gibson, MD, PhD
- Data Exploration at MetroHealth David Kaelber, MD, PhD
- Innovation and localization of data analytics at VA Sarah Russell, MD, MBA
- Text and waveform (big data) analytics at Stanford Children's Jon Palma, MD, MS and Veena Goel, MD
- Complex event processing Sameer Badlani, MD
- Panel Q&A 30 mins

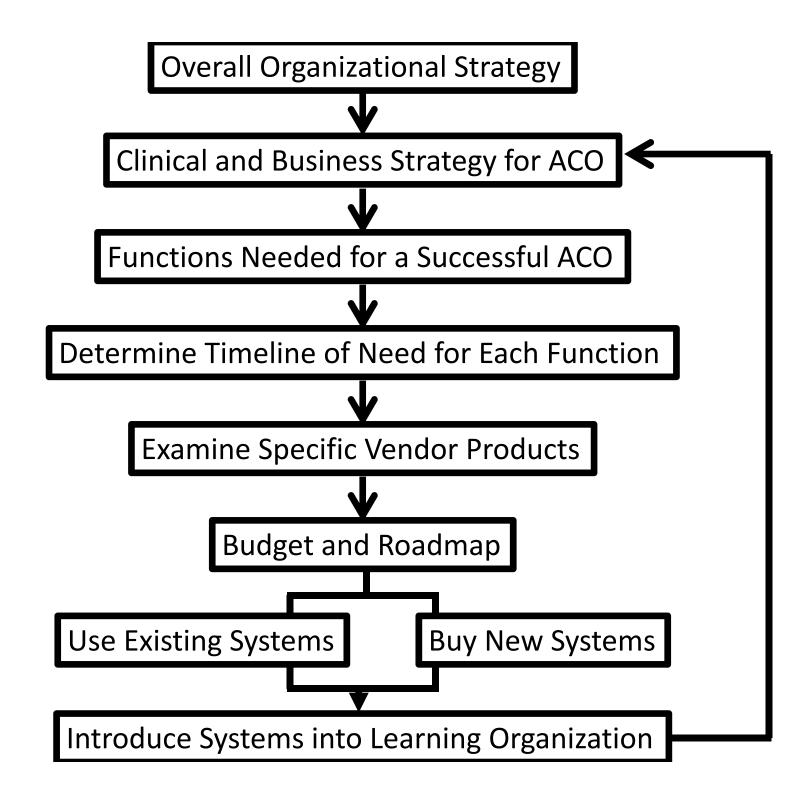
# Information Technology for Population Health Management

The Physician Computer Connection

AMDIS – Ojai

Thursday, 19 June 2014

Dick Gibson MD PhD
Portland OR



# Major Functions of Population Health Management

- Provider Record of Care
- Patient & Family-facing Functions
- Attribution
- Risk Identification
- Group Tracking
- Care Planning
- Care Management
- Patient Outreach
- Performance Reporting
- Financial Management

#### Provider Record of Care

- Each professional has system to record useful information about the encounter, evaluation, or action taken
- Each professional can see the records of the other professionals either by viewing or importing (say with HIE)

#### Patient & Family-facing Functions

- Allows patient & family to enter their own data and respond to surveys
- Includes outcome analytics of value for the patient & family
- Includes report cards on providers and facilities
- Assists patient and family decision-making

#### Attribution of Patients to Providers

- Algorithm options: based on number of visits with primary care, most recent visit, intensity, total payments, CMS attrib
- Algorithms are transparent to providers

#### Risk Identification

- Which patients are most likely to get ill?
- Which patients would benefit most from intervention?
- What intervention is indicated?
- Will that intervention make a difference in outcome?

#### **Group Tracking**

- Identify patients by age, diagnosis, procedure, medication, labs, habits, health risk assessment, preventive care
- Updated promptly by action charted in EHR
- Single-patient report is viewable within EHR visit workflow
- Multi-patient reports are easily accessible

#### Care Planning

- The clinical content of Care Management
- For a given indicator/diagnosis, what is indicated to be done?
- Which providers need to do what by when?
- What does a given provider need to do today at the office visit

#### Care Management

- EVERY patient gets it
- may be done intermittently
- results in a single approved care plan
- done by clinical personnel
- same as Care Coordination

#### Case Management

- only SOME patients get it
- provided continuously
- assists with coordination of services
- assists with daily living skills
- assists with finding & maintaining housing, jobs, friends
- may provide transportation
- done by professionals and paraprofessionals

#### Care Management

- Organized by Care Goals and Long-term Care Plan
- Imports data from and sends data to Provider Record of Care
- Captures charting by Care Managers and Case Managers
- Uses the clinical content of the Care Planning system

#### Patient Outreach

- Manual selection of patients
- Automatic patient selection based on Group Tracking
- Manual deselection when contact would be inappropriate
- Library of campaign messages based on condition

#### Performance Reporting

- Patient clinical and financial outcomes by provider
- Provider productivity
- Identify providers to be coached, join, or leave network
- Ability to compare performance to benchmarks

#### Financial Management

- Cost of care analysis
- Analysis to negotiate contracts with providers and payers
- Out of network costs
- Benefit design and premium calculation

#### The Functions Overlap



Data Types	Data کرین	a Sc	ourc	es inter	iling of the	in oc	To the state of th	Rest of Section Sectio	16 80 S	COUNTY OF THE STATE OF THE STAT	ALL STORY	all'of	of the state of th	Siles Siles	ding	Stry Mes
Age or date of birth	х	х	х	х	x	х	х	х	Х	x	X	Х	Х	X		
Address, zip, census	х	X	X	х	х	X	X	X	Х	X	X	X	X	X		
Ethnic background	х	X	X	X			X			х	X			X		
Prior visit providers	X	X	X	X						X	X					
Prior visit cost			X	X						х	X					
History of current pr	х	X														
Health & risk habits	X	X					X									
Occupational history	X	X					Х			X		X				
Work absences		X					X					X				
Family history	X	X					X									
Prior surgeries	X	X	X	Х			Х			X	Х					
Problem list	х	X	X	X	X	х	X			X	X					
Medication list	X	X		х	х	х	X				X					
OTC medications	х	X			х	X	X						X			
Allergies & intolerar	х	X			х	х	Х									

System —	<b>&gt;</b> EHR	Registry	Care MgtRec	Analy- tics	Manual Work	•••
Provider Record	+++		+			•••
Patient Facing	+/++		+			•••
Attribution			+	+++		•••
Risk Ident	+	++	+	+++	+	•••
Group Tracking	++	+++	+/++	++/+++	+	•••
Care Planning	+/++	+/++	++/+++		+	•••
Care Managemt	+/++		+++			
Patient Outreach	++/+++		?		++	•••
Perform Report	+	+	+	+++	+	•••
Financial Mgt				+++	+	•••

#### Year 3 Year 2 Year 1

System — Function Provider Record	CHK	Registry	~ulb		<b>/</b>	<u> </u>	
Patient Facing			MgtRec	Analy- tics	Manual	.,	
Attribution	+/++		+		Work		
Risk Ident			+			•••	
Group Tracking	+	++	+	+++		•••	
Care Planning		+++	+	+++	+	•••	
Care Managemt	717	+/++	+/++	++/+++	+	•••	
Patient Outreach	+/++		++/+++		+	•••	
Perform Report	++/+++		+++		T	•••	
Financial	+	+	3		1.		
Financial Mgt			+	+++	++		
				+++	+		

#### Questions?

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# Data Exploration @ MetroHealth (3 cases)

David C Kaelber, MD, PhD, MPH, FAAP, FACP

Board Certified in Clinical Informatics
Associate Professor of Internal Medicine, Pediatrics, Epidemiology, and Biostatistics
Director of the Center for Clinical Informatics Research and Education
Chief Medical Informatics Officer
The MetroHealth System
Case Western Reserve University





# MetroHealth and EHR (Epic)

#### **System Overview**

- 1 tertiary care academic hospital
- 21 outpatient facilities
- 300+resident/fellow physicians
- 500 staff physicians
- 1,200 nurses
- 30,000 inpatient stays/year
- 100,000 ED visits/year
- 1,000,000 outpatient visits/yr
- Affiliated with Case Western Reserve University
- Public healthcare system for Cuyahoga County

- 1999 Ambulatory EHR (EpicCare w/ Cadence, Prelude, & Resolute)
- 2004 EHR in ED (ASAP)
- 2009 Inpatient EHR (Epic w/ Inpatient Willow and Beacon
- 2011 CareEverywhere, e-Rx, MyChart, Nurse Triage
- 2012 Epic Enterprise Contract, MU Stage 1
- 2013 BCMA, EpicCare Link, Welcome
- 2014 ADT, Bedtime, OpTime, SBO, Research



#### Total EHR data

- 1 million patients
- · 15 million visits
- 120 million labs/pathology
- 750,000 imaging studies
- 15 years of data in Epic

1st public healthcare system in US to install Epic in the outpatient setting!!! 1st public healthcare system in US with Epic to achieve HIMSS Stage 7 EMRAM Ambulatory (5/14)!!!

# Case #1 - Pediatric Hypertension













# Case #1 - Pediatric Hypertension

Blood Adult

Pressure

Normal SBP ≤120 and/or DBP ≤80

Pre- SBP >120 and ≤139 and/or

hypertensive DBP >80 and ≤89

Stage I HTN SBP >139 and ≤159 and/or

DBP >89 and ≤99

Stage II HTN SBP > 159 and/or DBP > 99

Children

SBP and/or DBP < 90% for gender, age, and height

SBP and/or DBP ≥ 90% and < 95% for gender, age, and height

SBP and/or DBP ≥ 95% and ≤ 99% +5mmHg for gender, age, and height

SBP and/or DBP > 99% +5mmHg for gender, age, and height

Need 3 measurements for diagnosis of hypertension (HTN) or prehypertension (preHTN).





# Case #1 - Pediatric Hypertension





*JAMA*. 2007;298(8) :874-879

AHA Top 10 Research Advance of 2007!

Ladies' Home Journal Healthcare Breakthrough Award of 2008!





# Case #2 - Referral Completion

"The MetroHealth System is not reaching its financial revenue targets because expected patient volumes are down in both primary care and specialty care."

- MetroHealth CEO (summer 2011)





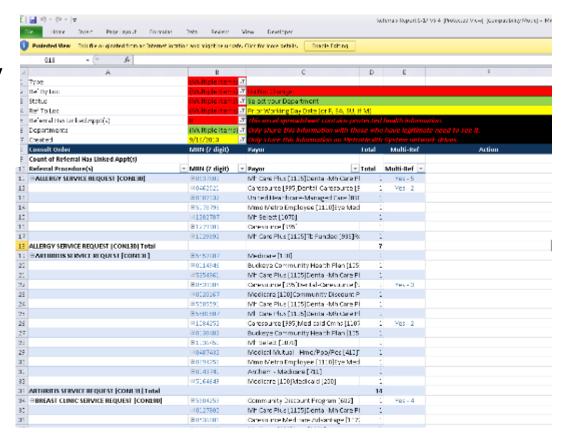


# **Case #2 - Referral Completion**

Consults/procedure orders written yesterday not completed or scheduled today.

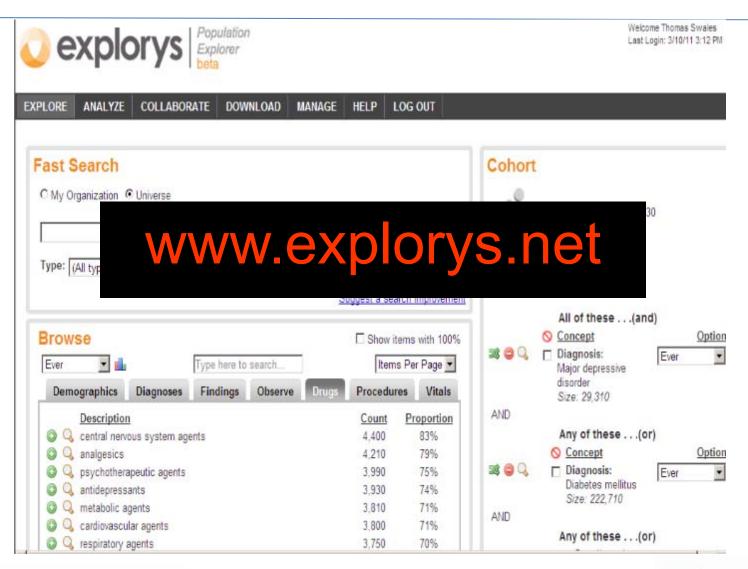
After 12 months (2/2012-2/2013) the 30-day consult and procedure completion/schedule rate went from 48% to:

Answer: 61%



~6700/month additional initial consults (61,939) and procedures (18,936) completed/scheduled (and ~\$1,000,000/month in new gross revenue).









- Pooled, normalized, standardized EHR data
- Over 40 million patients (6/17/2014; growing)
- Web interface (Google-like speed)
- Data Types
  - Demographic (gender, age, race/ethnicity, insurance, zip-3)
  - Diagnoses (ICD-9, SNOMED-CT)

Unified Medical Language System (UMLS)

Example – Post-market drug surveillance of Azathioprine (relatively rarely used drug with rare side effect); are side effects more/less or the equivalent to similar drugs





## Side Effects Investigated

Side Effect	Lab Value	Abnormal Range
Anemia	Hemoglobin (Hgb)	<11 g/dL
Cell lysis	Lactate dehydrogenase (LDH)	>190 IU/L
Fever	Temperature	>37.8°F
Hepatotoxicity	AST, ALT	AST>40 IU/L and ALT>40 IU/L
Hepatotoxicity	Total bilirubin (Bili)	>1 mg/dL
Hypertension	Blood pressure (BP)	Systolic >140 mm Hg or Diastolic>90 mm Hg
Nephrotoxicity	Creatinine (Cr)	>1.5 mg/dL
Neutropenia	Neutrophil count	Count<57% or <2.5 cells/μl
Neutrophilia	Neutrophil count	Count>70%





## Side Effects Investigated

Side Effect	Lab Value	Abnormal Range
Anemia	Hemoglobin (Hgb)	<11 g/dL
Cell lysis	Lactate dehydrogenase (LDH)	>190 IU/L
Fever	Temperature	>37.8°F
Hepatotoxicity	AST, ALT	AST>40 IU/L and ALT>40 IU/L
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Nephrotoxicity	Creatinine (Cr)	>1.5 mg/dL
Neutropenia	Neutrophil count	Count<57% or <2.5 cells/μl
Neutrophilia	Neutrophil count	Count>70%





Control cohort administered one of 12 anti-rheumatic drugs. Overlap is evident between the cohorts since controlling the AZA cohort for the absence of the other 12 drug.

Drug Name (RxCUI)	Contro	l Cohort		AZA Cohort
Abatacept (614391)	140	(0.1%)	60	(0.4%)
Adalimumab (327361)	2660	(2.1%)	650	(4.7%)
Azathioprine (1256)	3610	(2.8%)	13890	(100.0%)
Clioquinol (5942)	110	(0.1%)	0	(0.0%)
Etanercept (214555)	2490	(1.9%)	250	(1.8%)
Homatropine (27084)	66170	(51.1%)	680	(4.9%)
Hydroxychloroquine (5521)	22900	(17.7%)	2000	(14.4%)
Infliximab (191831)	2880	(2.2%)	1200	(8.6%)
Iodoquinol (3435)	7350	(5.7%)	80	(0.6%)
Leflunomide (27169)	1460	(1.1%)	480	(3.5%)
Methotrexate (6851)	17710	(13.7%)	1750	(12.6%)
Oxyquinoline (110)	220	(0.2%)	0	(0.0%)
Sulfasalazine (9524)	5320	(4.1%)	570	(4.1%)
Total	129560		13890	



#### Results

% of patients with comorbidities induced by AZA. Diagonal represents the proportion of patients experiencing a single side effect. Relative risk of developing a comorbidity (relative to any one of 12 anti-rheumatic drugs) is indicated by the cell color.

		Cr	AST, ALT	Bili	Neutro- penia	Neutro- philia	Temp	BP	Hgb	LDH
	Cr	7.9%	30.8%	7.7%	15.4%	38.5%	53.8%	53.8%	69.2%	30.8%
	AST, ALT	19.0%	14.1%	33.3%	9.5%	23.8%	33.3%	14.3%	47.6%	19.0%
;	Bili	4.5%	31.8%	14.1%	9.1%	45.5%	27.3%	36.4%	45.5%	13.6%
Effect	Neutropenia	2.4%	2.4%	2.4%	24.3%	0.0%	4.7%	8.2%	7.1%	0.0%
ury E	Neutrophilia	3.6%	3.6%	7.3%	0.0%	45.2%	7.3%	13.9%	18.2%	7.3%
Primary	Тетр	15.6%	15.6%	13.3%	8.9%	22.2%	13.1%	60.0%	55.6%	4.4%
7 1	ВР	4.6%	2.0%	5.3%	4.6%	12.5%	17.8%	29.5%	20.4%	2.0%
	Hgb	16.1%	17.9%	17.9%	10.7%	44.6%	44.6%	55.4%	28.4%	19.6%
	LDH	30.8%	30.8%	23.1%	0.0%	76.9%	15.4%	23.1%	84.6%	59.1%

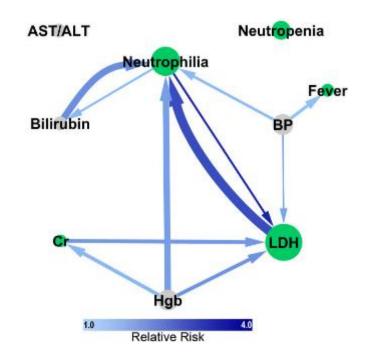






#### Results

<u>V Patel</u> and **DC Kaelber**. *Using Aggregated, De-Identified Electronic Health Record Data for Multivariate Pharmacosurveillance: A Case Study of Azathioprine*. <u>Journal of Biomedical Informatics</u> (Special Clinical Research Informatics issue). 2013 Oct 28. pii: S1532-0464(13)00161-5. [Epub ahead of print] PMID:24177317.



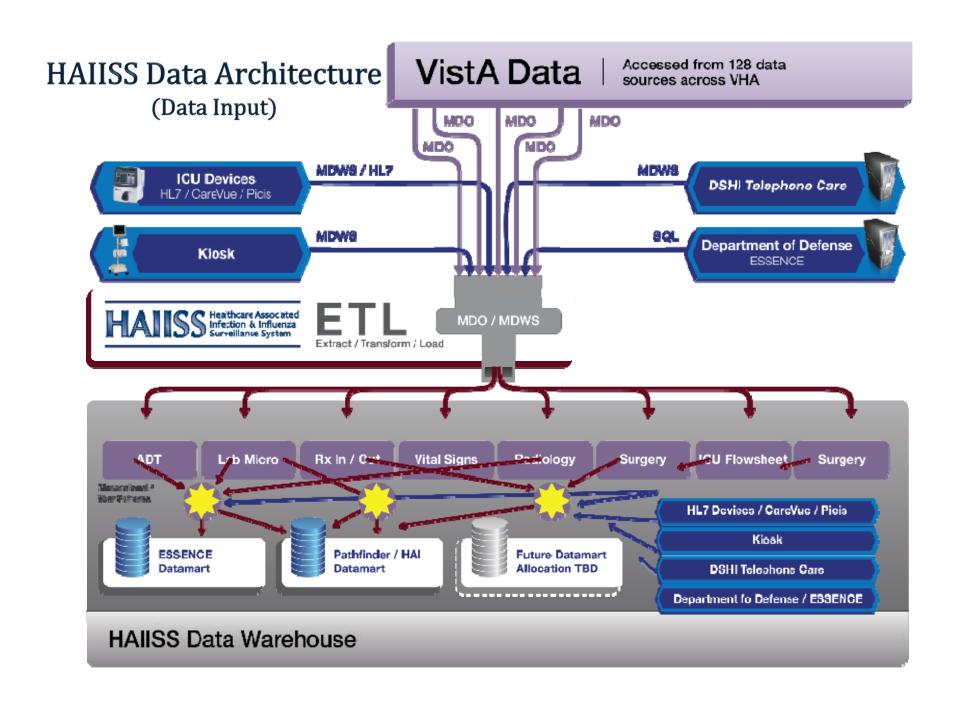




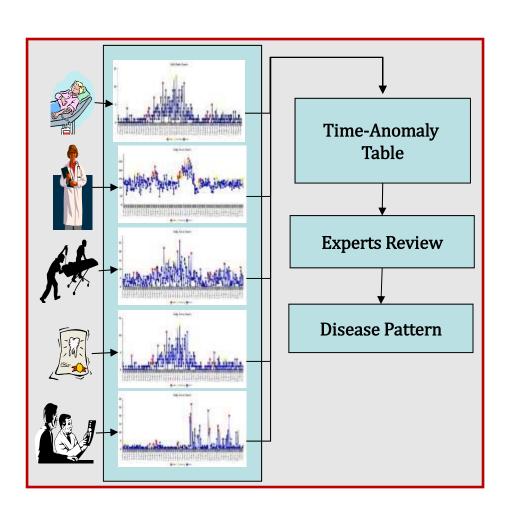
# VA Clinical Informatics: Four programs highlighting advances and innovation in analytics

Sarah Russell, MD
<a href="mailto:sarah.russell@va.gov">sarah.russell@va.gov</a>
CMIO, VA Palo Alto Healthcare System

- Clinical data driving bio-surveillance
- Corporate data warehouse and dashboards
- Patient engagement analytics
- Machine learning and free text analysis of the medical record



# Surveillance system approach

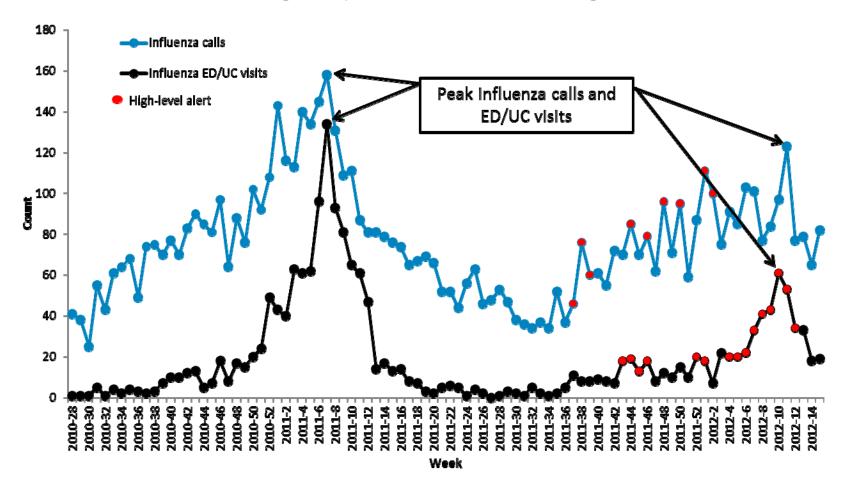


Step one: pull from heterogeneous data sources

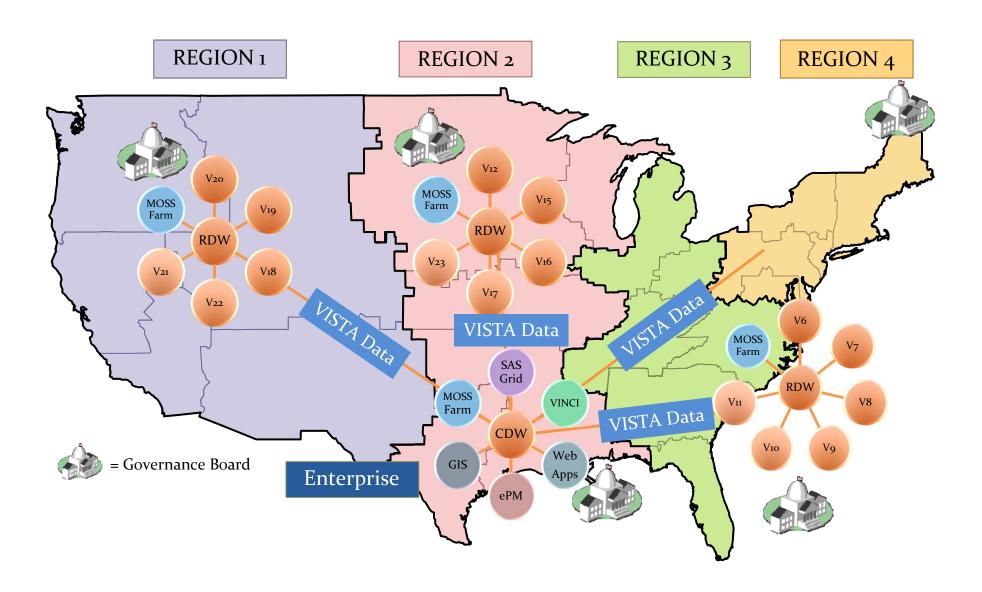
Step two: do temporal analysis – with focus on anomalies

Step three: expert evaluates pattern and determines relevance given objectives

# VA telephone encounter data for influenza ICD-9-CM coded calls and emergency department/urgent care visits



#### Corporate data warehouse



### Corporate data warehouse:

#### unique applications in pharmacy

- 🖃 🛐 Dim.LocalDrug
  - 🖃 🛅 Columns
    - 🔳 LocalDrugSID (int, not null)
    - 🔳 LocalDrugIEN (varchar(50), not null)
    - 🔳 Sta3n (smallint, not null)
    - 🔳 LocalDrugNameWithDose (varchar(100), null)
    - 🔳 NonFormularyFlag (char(1), null)
    - 🔳 InactivationDate (date, null)
    - DEAHandling (varchar(10), null)
    - MaxDosePerDay (varchar(50), null)
    - MaxDosePerDayNumeric (numeric(9,4), null)
    - OrderUnit (varchar(3), null)
    - 🔳 PricePerOrderUnit (smallmoney, null)
    - DispenseUnitsPerOrderUnit (varchar(20), null)
    - PricePerDispenseUnit (smallmoney, null)
    - CMOPDispenseFlag (char(1), null)
    - VAClassification (varchar(10), null)
    - BestDrugClass (varchar(10), null)
    - NationalDrugIEN (varchar(50), null)
    - NationalDrugSID (int, null)
    - DrugNameWithoutDose (varchar(100), null)
    - 🔳 ETLBatchID (int, null)
    - VistaCreateDate (datetime, null)
    - 🔳 VistaEditDate (datetime, null)

#### Medication Safety

	Actual	Target	Not Met	Patients	Definition
Dashboard Instructions					Definition
<b>□ Amiodarone</b>	60.3%	62% 🛆		1,156	Definition
Amiodarone - LFT < 6 Months	64.9%	68% 🦲	406		
Amiodarone - TSH < 6 Months	55.6%	55%	513		
<b>☐ Azathioprine</b>	69.2%	72% 🦲		164	Definition
Azathioprine - CBC < 3 Months	60.4%	70% 🤷	65		
Azathioprine - LFT < 6 Months	78.0%	76% 🔵	36		
<b>□</b> Carbamazepine	68.1%	72% 🦲		689	Definition
Carbamazepine - CBC < 12 Months	81.3%	85% 🦲	129		
Carbamazepine - Level < 6 Months	26.0%	29% 🤷	510		
Carbamazepine - LFT < 12 Months	81.6%	86% 🦲	127		
Carbamazepine - Sodium < 12 Months	83.5%	88% 🦲	114		
□ Glyburide (65 y/o or older)	90.2%	91% 🦲		2,681	Definition
Glyburide - SCr < 2 if at least 65 y/o	90.2%	91% 🦲	263		
□ Leflunomide	64.8%	78% 🤷		135	Definition
Leflunomide - CBC < 3 Months	65.9%	79% 🤷	46		
Leflunomide - LFT < 3 Months	63.7%	77% 🤷	49		
□ Lithium	74.3%	76% 🦲		896	Definition
Lithium - CBC < 12 Months	83.3%	85% 🦲	150		
Lithium - Level < 12 Months (at least 900mg/d)	81.7%	87% 🦲	99		
Lithium - SCr < 12 Months	89.5%	91% 🦲	94		
Lithium - TSH < 6 Months	50.2%	55% 🦲	446		
H Marcantonurina	75 NO/-	040/- 📤		02	Dofinition

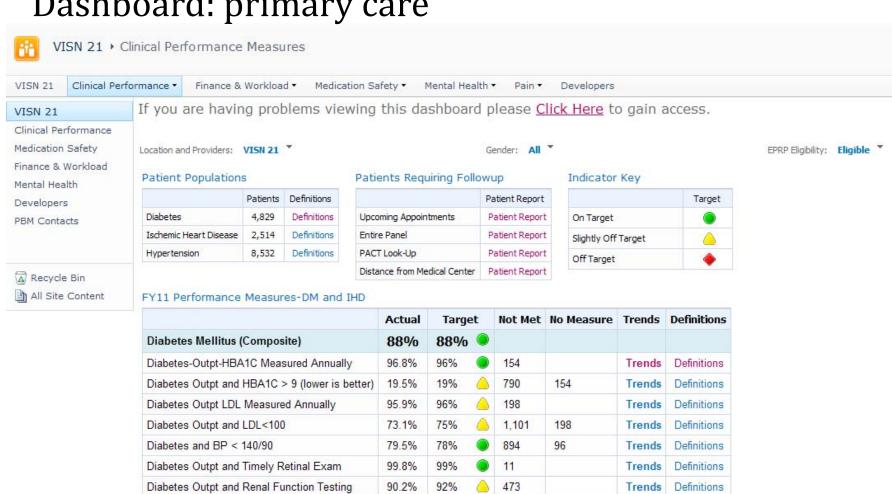
#### Dashboard: primary care

Ischemic-Heart-Disease

IHD - Outpt LDL Measured Annually

IHD - Patients with LDL < 100

Hypertension and BP < 140/90



94.9%

74.2%

77.3%

92%

69%

72%

128

521

1,789

128

152

Definitions

Definitions

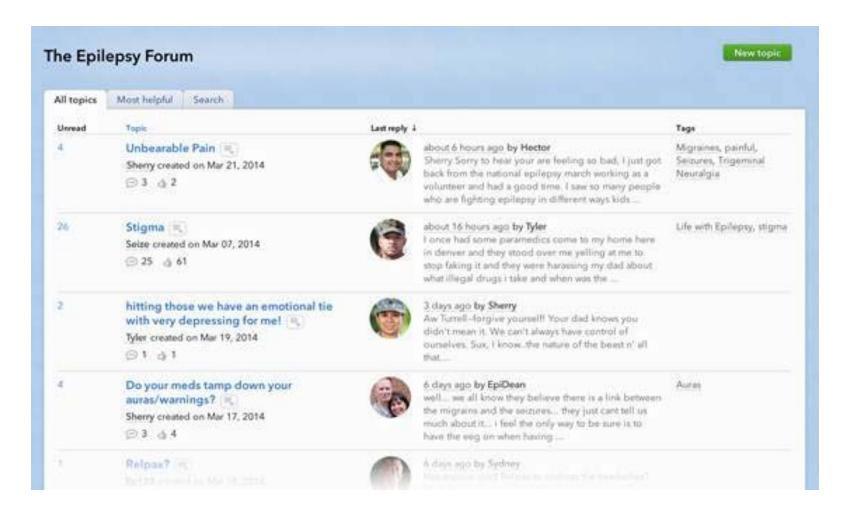
Definitions

Trends

Trends

Trends

#### Patient engagement analytics

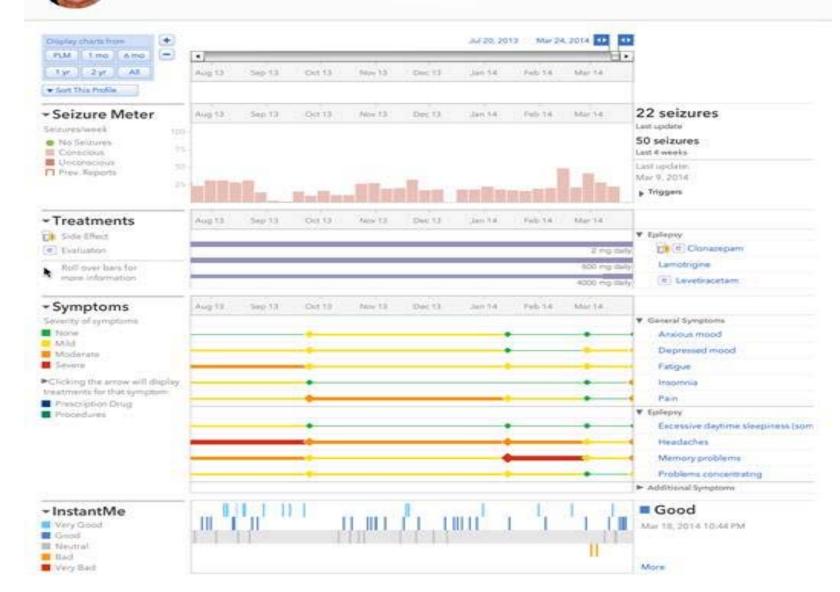


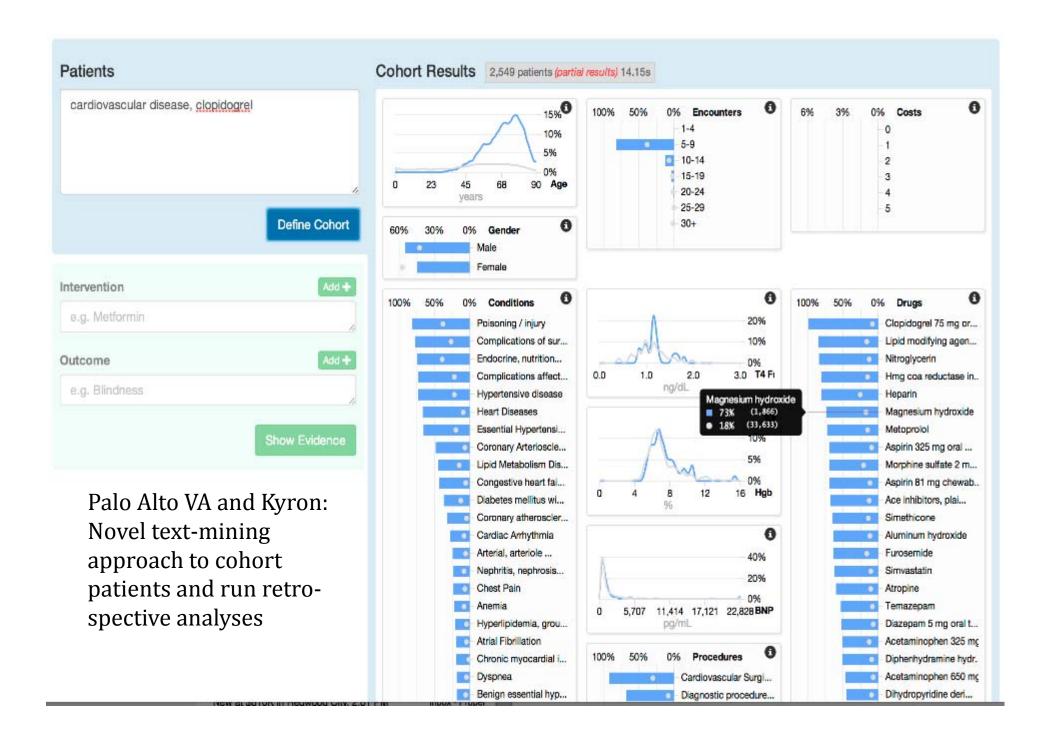
Primary Condition: Epilepsy and 1 more ▼

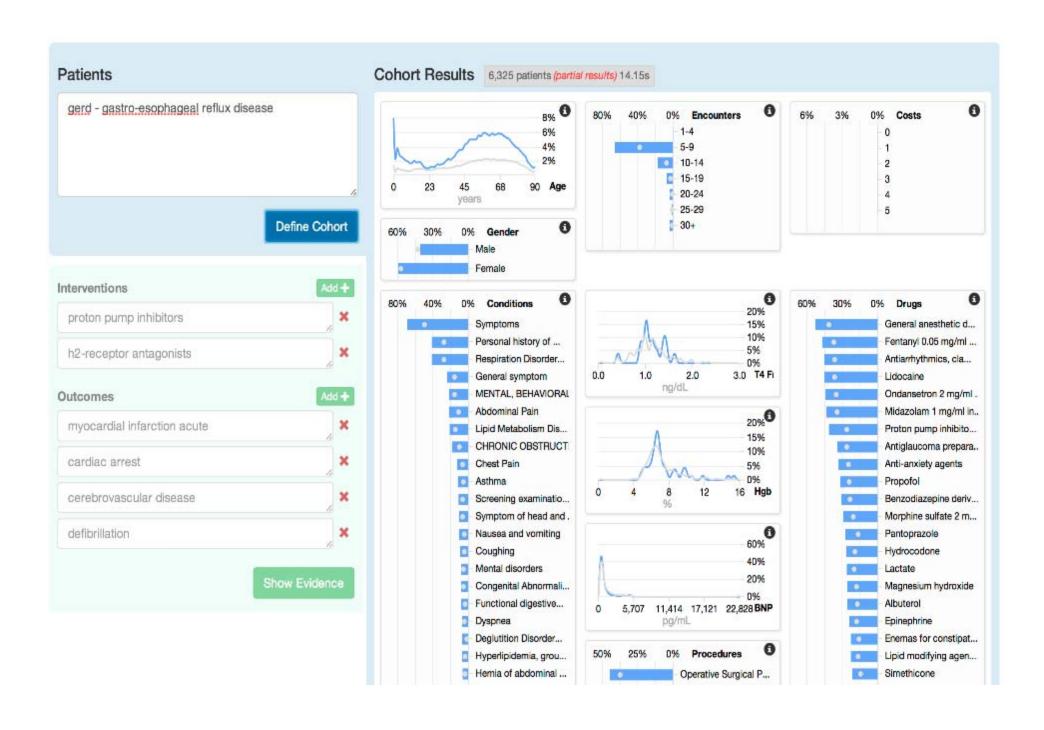
First seizure: Oct 1980 • Diagnosis: Oct 1980

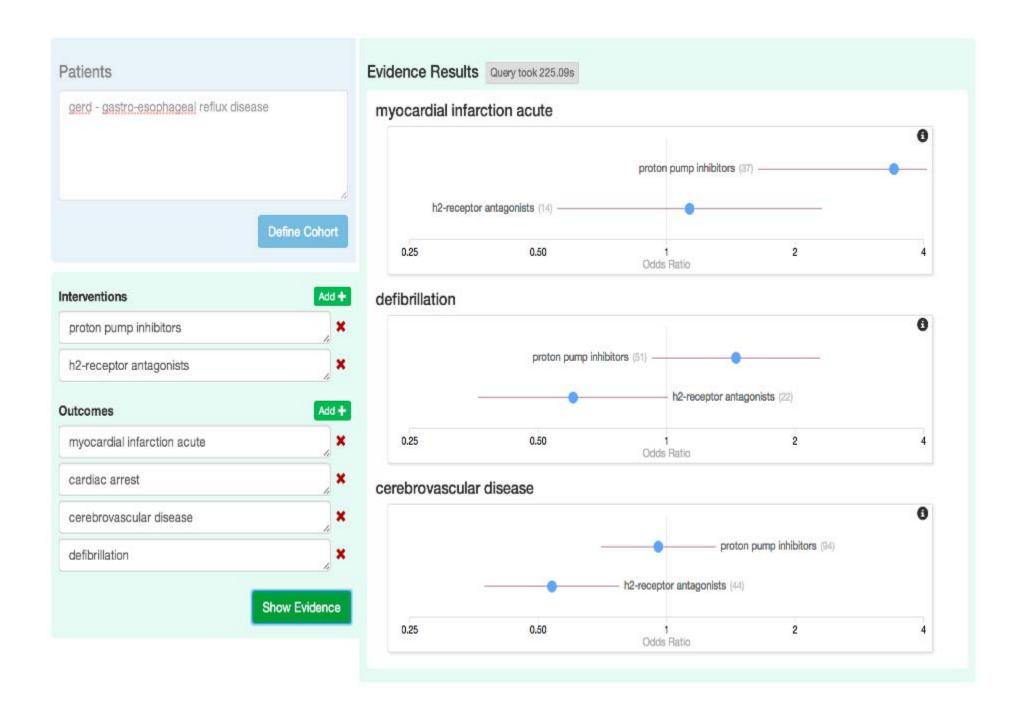
Interests: Faith

▶ See more









# Text Analytics at Stanford Children's Health

Jonathan Palma, MD, MS

AMDIS Physician-Computer Connection Symposium

19 June 2014





## Proofs of Concept

- IBM Content Analytics
  - Watson-like NLP technology
  - Search/analytics application
  - Use case-specific content
- HP Autonomy Healthcare Analytics
  - IDOL statistical inference algorithms
  - Combined with medical terminologies
  - Web-based search application





## HP Autonomy Pilot

 Business Owners: Quality and Clinical Effectiveness Team

Use Case: US News and World Report Survey







## HP Autonomy Pilot

- Clinical data from 2011 2013
  - ~115k patients, ~390k encounters, ~3 million documents
- Structured
  - Patient ID, age
  - Encounter ID, location
  - Diagnosis (ICD) and Procedure (CPT) codes
  - Document metadata (e.g. author, attending provider)
- Unstructured
  - Clinical documents
  - Radiology reports





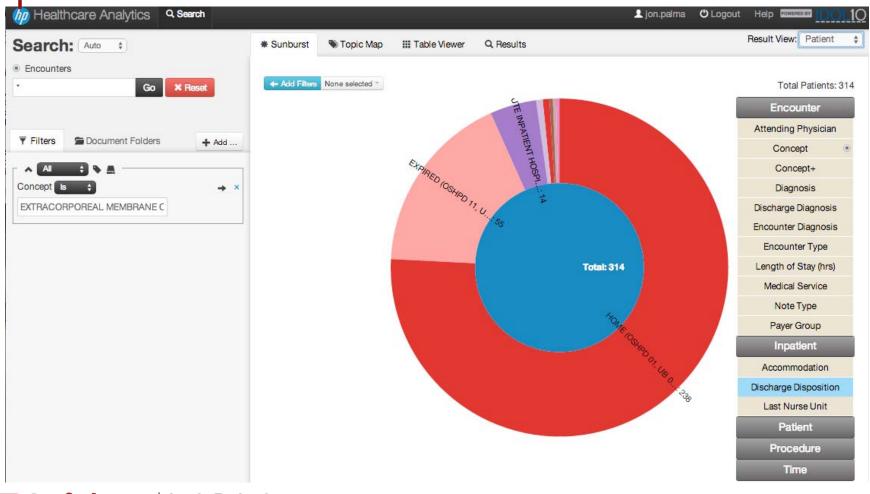
# HP Autonomy Healthcare Analytics: Core Functions

- Cohort Identification
- Chart Abstraction
- Advanced Analytics





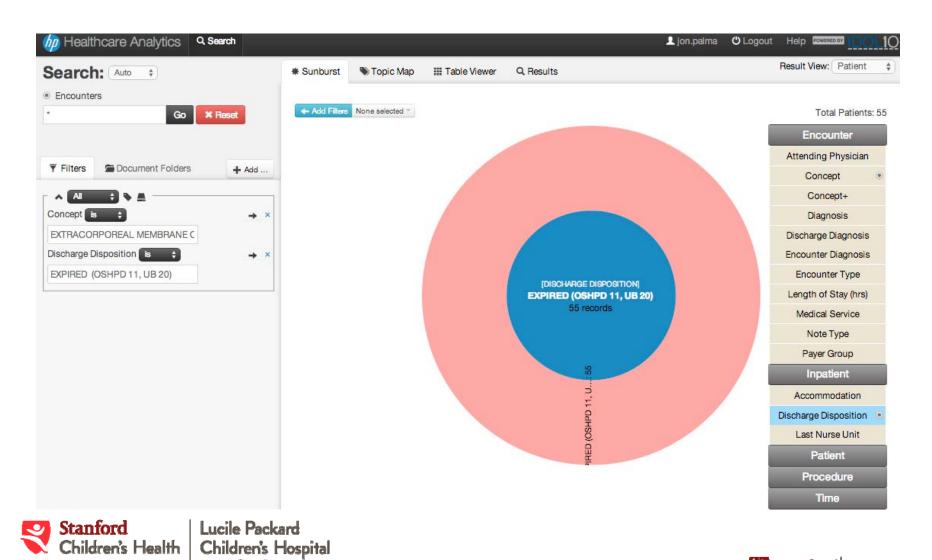
# Concept search (SNOMED) for ECMO patients







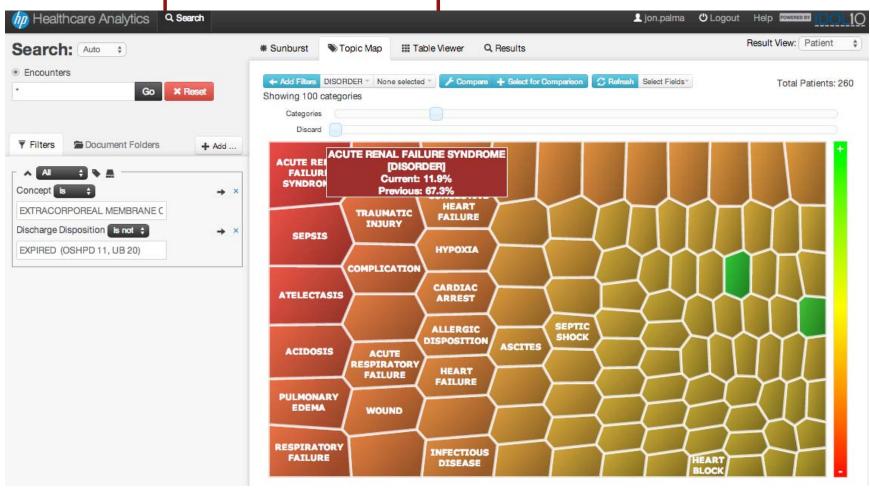
## ECMO patients with disposition "Expired"



Stanford



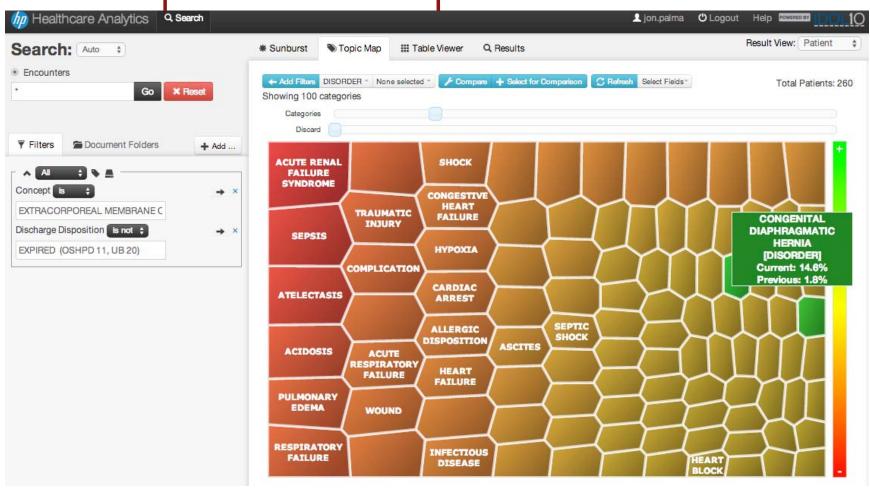
# Comparison of Expired vs. non-Expired ECMO patients







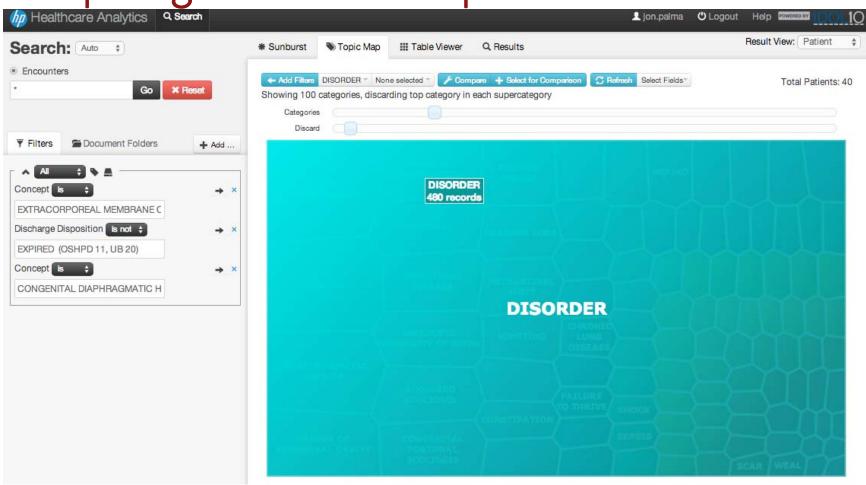
# Comparison of Expired vs. non-Expired ECMO patients







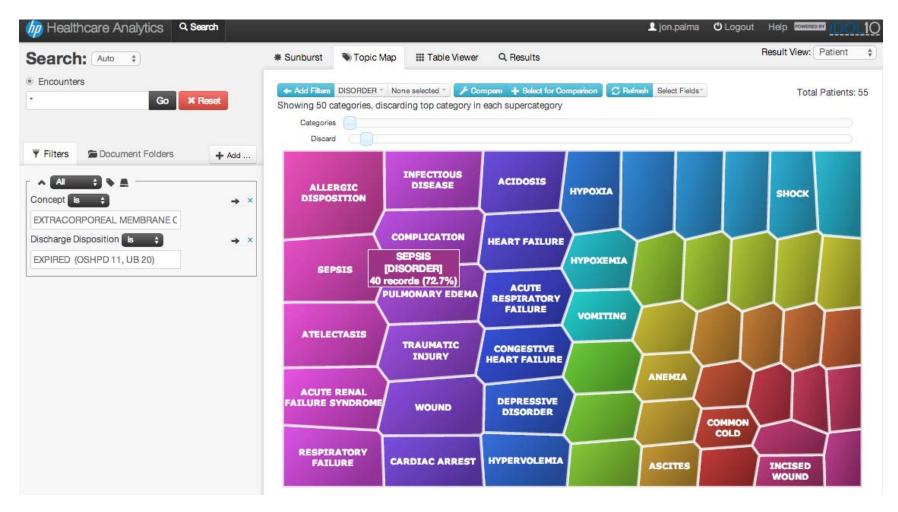
# Additional Filter for Congenital Diaphragmatic Hernia patients







## Topic Map of Expired ECMO patients







# HP Autonomy Healthcare Analytics: Current Use

- Venous Thromboembolism (Cohort Identification, Chart Abstraction)
- Surgical Site Infections (Cohort Comparison)
- Investigation of other Hospital Acquired Conditions
- Identification of process and outcomes measures
- Development of standardized care protocols





# HP Autonomy Healthcare Analytics: Future Directions

- Availability to service chiefs, medical staff
  - Self service analytics tool
  - Security/Privacy considerations
- Facilitate traditional research
- Support the concept of a Learning Healthcare System
  - Insight into past experience (i.e. practice-based evidence)
  - Allow for increasingly data driven care decisions







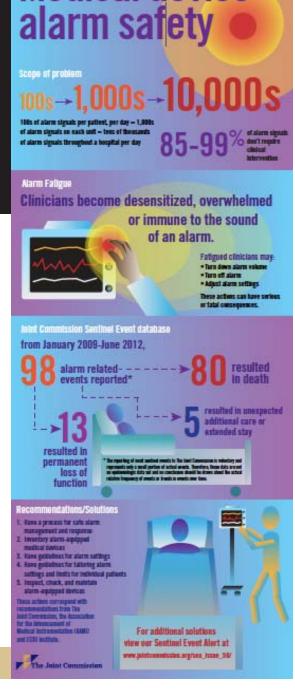
# An Application of "Big Data Analytics" at Stanford Children's: Bedside Monitor Alarm Fatigue

Veena Goel, M.D. Fellow in Clinical Informatics and Pediatric Hospital Medicine



## The Joint Commission Sentinel Event Alert

Joint Commission Sentinel Event Alert #50 April 8, 2013



Medical device



# Medical device alarm safety

Scope of problem

 $100s \rightarrow 1,000s \rightarrow 10,000s$ 

100s of alarm signals per patient, per day = 1,000s of alarm signals on each unit = tens of thousands of alarm signals throughout a hospital per day

85-99% of alarm signals don't require clinical intervention



Clinicians become desensitized, overwhelmed or immune to the sound of an alarm.



- Turn down alarm volume
- Turn off alarm
- Adjust alarm settings

These actions can have serious or fatal consequences.

#### **Joint Commission Sentinel Event database**

from January 2009-June 2012,

3 alarm related - - - - - > 8 0 resulted in death

->13

resulted in permanent loss of function resulted in unexpected additional care or extended stay

\* The reporting of most sentinel events to The Joint Commission is voluntary and represents only a small portion of actual events. Therefore, these data are not an epidemiologic data set and no conclusion should be drawn about the actual relative frequency of events or trends in events over time.



#### Impetus for change

- 2014 National Patient Safety Goal:
  - Phase 1 (2/2014): alarms to be established as an organization priority by all hospitals.
  - Phase 2 (2/2016): all hospitals expected to develop and implement specific policies and procedures and to educate organization members about alarm system management.



#### **Recommendations/Solutions**

- 1. Have a process for safe alarm management and response
- 2. Inventory alarm-equipped medical devices
- 3. Have guidelines for alarm settings
- 4. Have guidelines for tailoring alarm settings and limits for individual patients
- 5. Inspect, check, and maintain alarm-equipped devices

These actions correspond with recommendations from The Joint Commission, the Association for the Advancement of Medical Instrumentation (AAMI) and ECRI Institute.





For additional solutions view our Sentinel Event Alert at

www.jointcommission.org/sea\_issue\_50/



#### 1. Monitor less patients

- Epic EMR roll-out in May 2014
  - Changed patient admission order sets.
  - Unchecked default order to place patients on monitors.
- Working to determine 'best practices' around monitor use.
- Collaboration with and education of nursing management and staff.





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## 2. Data driven vital sign parameters

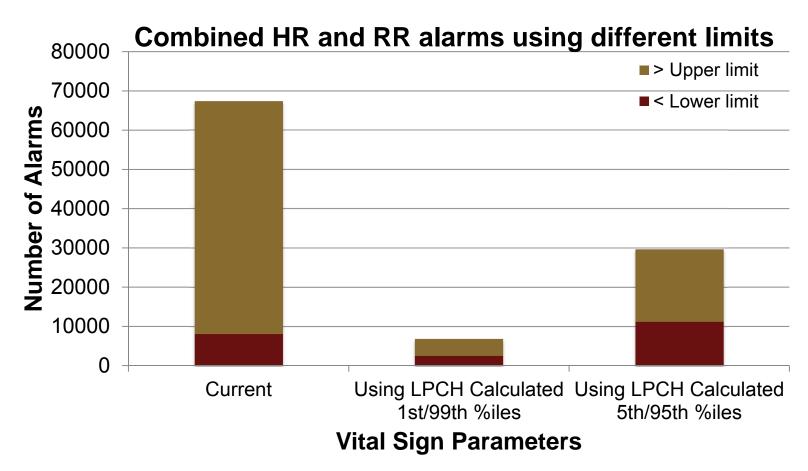


- Analysis of vital signs of hospitalized patients (stratified by age) in the calendar year 2013 at our institution to create percentile tables for heart rate (HR) and respiratory rate (RR).
- Modeled after work done by Bonafide et. al. (Pediatrics, 2013)
  - Created percentile curves for HR and RR of hospitalized children.
  - Found that 12-54% of HR observations and 32-40% of RR deviated from currently accepted ranges.



## Number of out-of-range HR & RR values in 2013 at LPCH

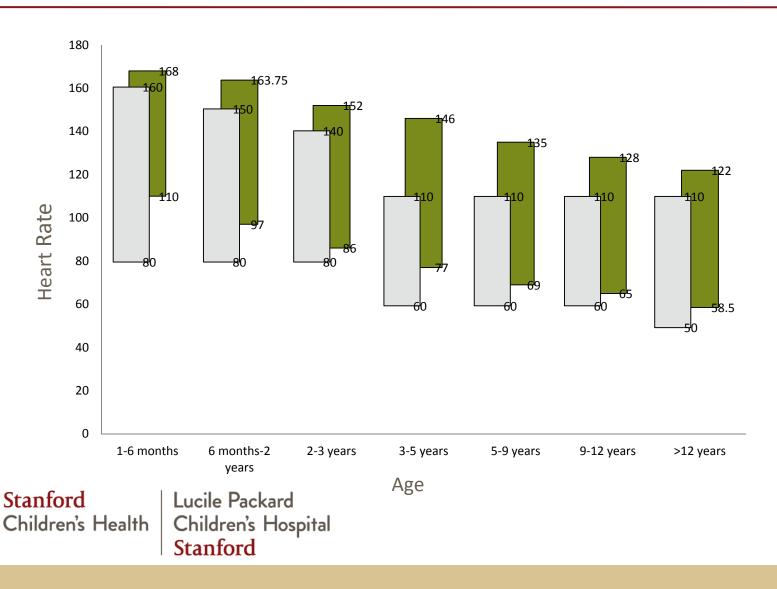






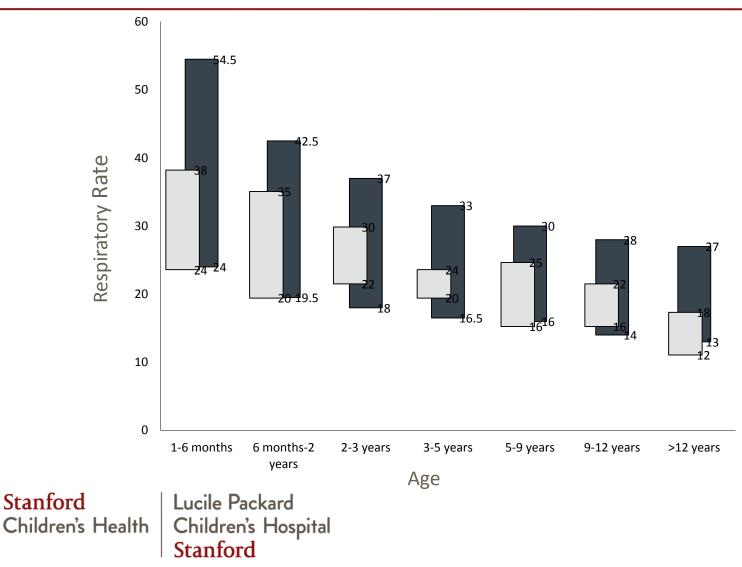
## Current vs. Proposed HR parameters by age





## Current vs. Proposed RR parameters by age





## Safety analysis of proposed new vital sign parameters



- Currently analyzing all rapid-response team calls and patient code events from 2013.
- Goal = to increase specificity of alarms while maintaining sensitivity.





## 3. Epidemiology of monitor alarms

- Unique data repository containing minute-by-minute monitor alarm and waveform data for all hospitalized patients since 2008.
  - RDE 'research data export' program links from the Philips monitors.
- Performing epidemiology analysis of alarms using this database.



## Thank you!



# Questions/Comments? Please contact me at: <a href="mailto:vvgoel@stanford.edu">vvgoel@stanford.edu</a>



Lucile Packard Children's Hospital Stanford



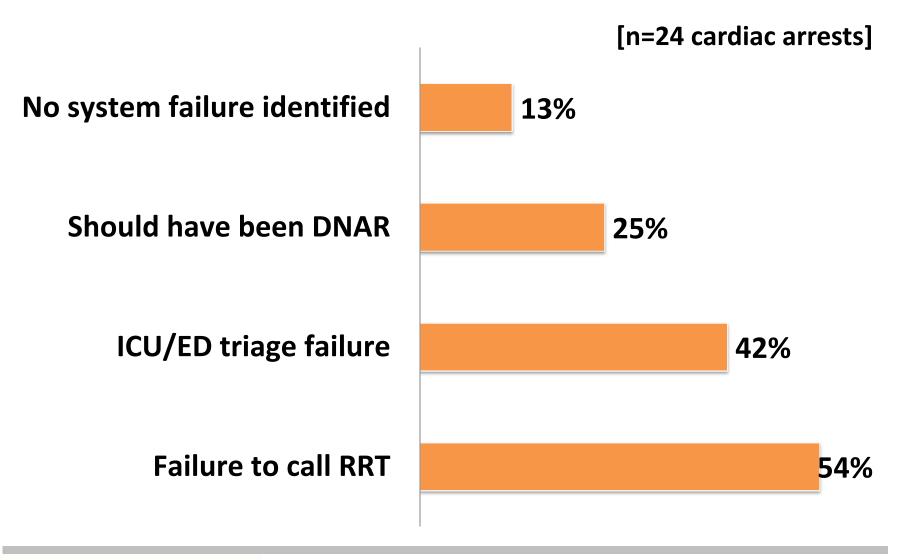
## **CEP Use Case**

Sameer Badlani, MD, FACP
CMIO
University of Chicago Medicine

#### **Disclosures**

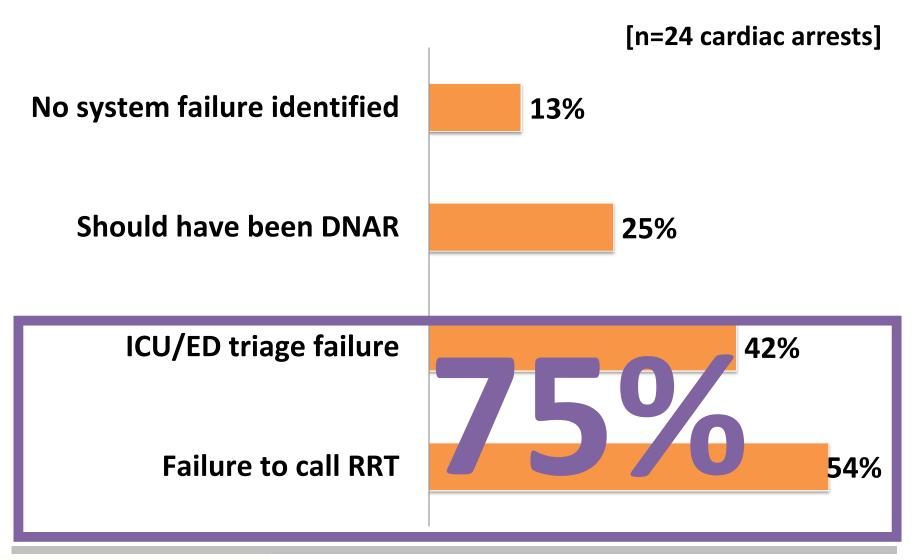
- The eCART algorithm is the intellectual property of the University of Chicago.
- The slides for the Cardiac Arrest algorithm are courtesy Dana Edelson, MD

## **January-April Ward Case Reviews**





## **January-April Ward Case Reviews**





## **Near Miss Analyis**

## Prolonged hypotension without RRT activation:

	0828	0830	0831	0835	0850	0900	0915	1000	1015	1030	1045	1100	1131	1145	1200	1215
Temp	35.6 (96		36.4 (97					36 (96.8)	35.9 (96			36.1 (97)	36 (96.8)		36.2 (97	
Temp Source	Tympanic		Tympanic					Tympanic	Tympanic			Tympanic	Tympanic		Tympanic	
Heart Rate/Pulse	86	88		84	91	85	85	91	96	94	93	88	85	80	77	78
Pulse Method																
Resp	20	22		15	17								20	20		
BP	70/34	70/37		70/35	73/41	72/45	75/43	75/48	82/52	81/41	78/48	85/49	82/43	77/36	83/48	84/46
MAP		45		43	48	52	50	55	60	51	54	58	51	45	56	53
MAP Method	Monitor												Monitor			
BP Method																
Position for BP																
SpO2	99			99	100	100	100						98			

## Using Electronic Health Record Data to Develop and Validate a Prediction Model for Adverse Outcomes in the Wards

Matthew M. Churpek, MD, MPH<sup>1,2</sup>; Trevor C. Yuen<sup>1</sup>; Seo Young Park, PhD<sup>3</sup>; Robert Gibbons, PhD<sup>2</sup>; Dana P. Edelson, MD, MS<sup>1</sup>

Objective: Over 200,000 in-hospital cardiac arrests occur in the United States each year and many of these events may be preventable. Current vital sign-based risk scores for ward patients have demonstrated limited accuracy, which leads to missed opportunities to identify those patients most likely to suffer cardiac arrest and inefficient resource utilization. We derived and validated a prediction model for cardiac arrest while treating ICU transfer as a competing risk using electronic health record data.

Design: A retrospective cohort study.

Setting: An academic medical center in the United States with approximately 500 inpatient beds.

Patients: Adult patients hospitalized from November 2008 until August 2011 who had documented ward vital signs.

Interventions: None.

Measurements and Main Results: Vital sign, demographic, location, and laboratory data were extracted from the electronic health record and investigated as potential predictor variables. A persontime multinomial logistic regression model was used to simultaneously predict cardiac arrest and ICU transfer. The prediction model was compared to the VitalPAC Early Warning Score using the area under the receiver operating characteristic curve and was validated using three-fold cross-validation. A total of 56,649 controls, 109 cardiac arrest patients, and 2,543 ICU transfers were included. The derived model more accurately detected cardiac arrest (area under the receiver operating characteristic curve, 0.88 vs 0.78;  $p \le 0.001$ ) and ICU transfer (area under the receiver operating characteristic curve, 0.77 vs 0.73;  $p \le 0.001$ ) than the VitalPAC Early Warning Score, and accuracy was similar with cross-validation. At a specificity of 93%, our model had a higher sensitivity than the VitalPAC Early Warning Score for cardiac arrest patients (65% vs 41%).

Conclusions: We developed and validated a prediction tool for ward patients that can simultaneously predict the risk of cardiac arrest

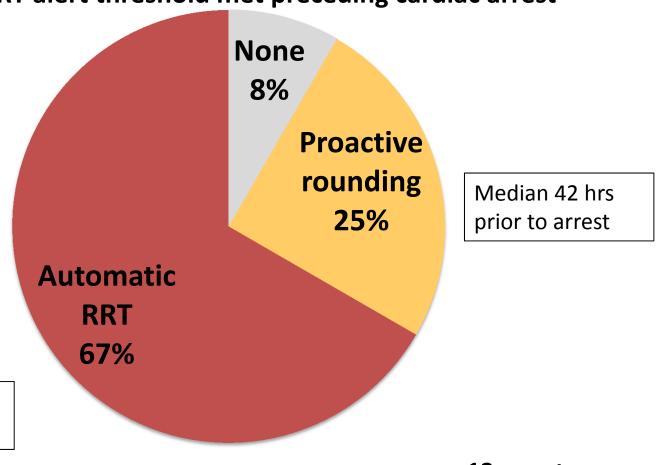
<sup>&</sup>lt;sup>2</sup>Department of Health Studies, University of Chicago, Chicago, IL.



<sup>&</sup>lt;sup>1</sup>Department of Medicine, University of Chicago, Chicago, IL.

## eCART Proof of Concept (Feb 2013 – Apr 2014)

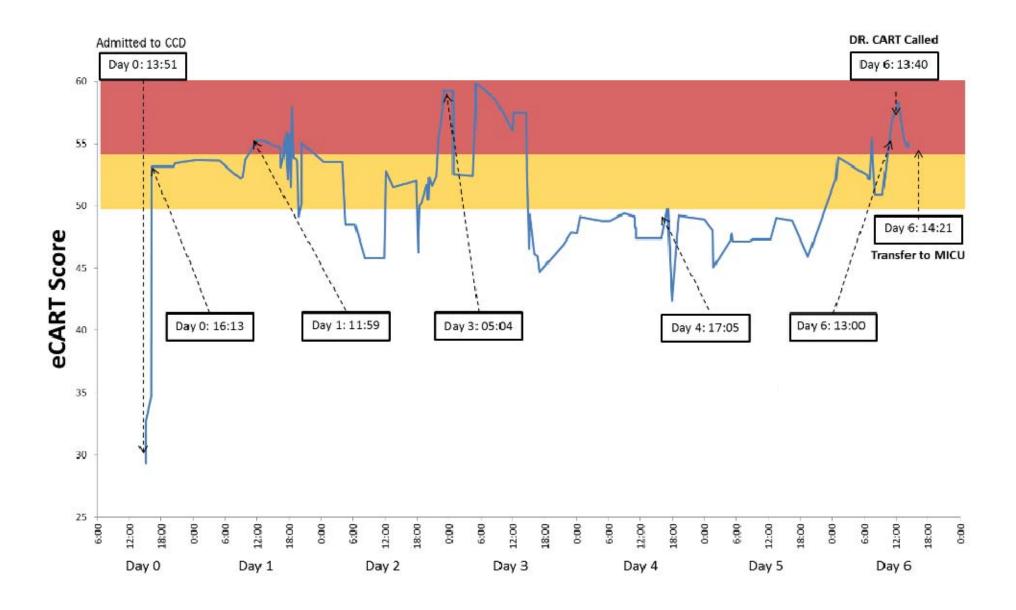




Median 30 hrs prior to arrest

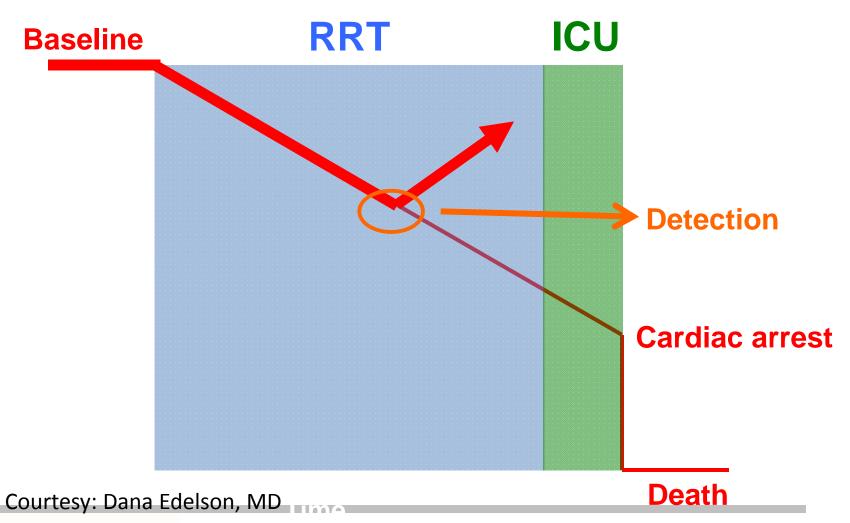
n=12 arrests







# Accurate detection of cardiac arrest may improve outcomes





### **Use Case**

#### Problem

- High rate of inpatient cardiac arrests
- Unpredictable yet if detected early based on physiological and other signals can lead to improved outcomes
- Data Available but no actionable intelligence
  - Continuous physiological and laboratory monitoring
  - EHR provides easy access but has unmanageable amount of data/information

#### Solution

- Real time statistical model to detect a possible cardiac event
- Use CEP engine to process information and alert on call physician
- Suggest actions



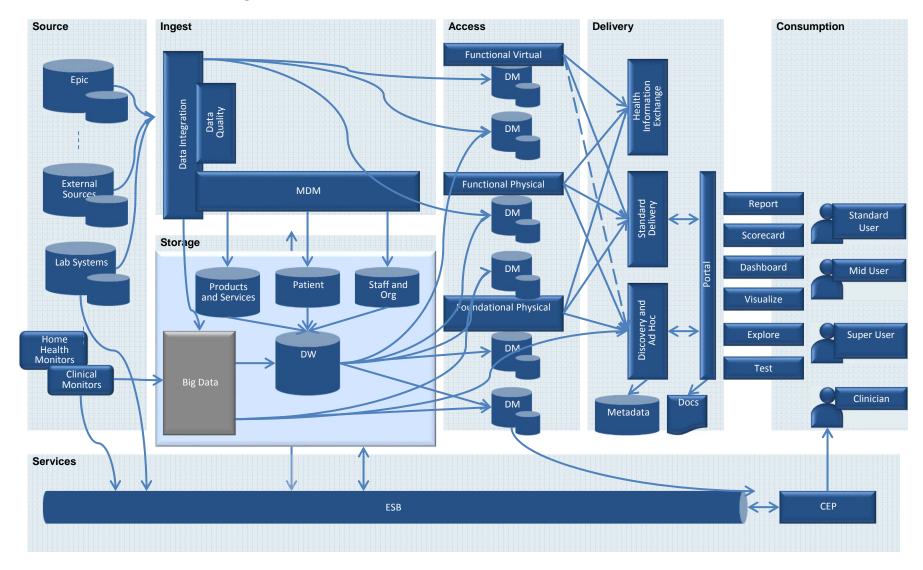
## **Complex Event Processing**

- Event processing is a method of tracking and analyzing (processing) streams of information (data) about things that happen (events),[1] and deriving a conclusion from them.
- Complex event processing, or CEP, is event processing that combines data from multiple sources[2] to infer events or patterns that suggest more complicated circumstances. The goal of complex event processing is to identify meaningful events (such as opportunities or threats)[3] and respond to them as quickly as possible.

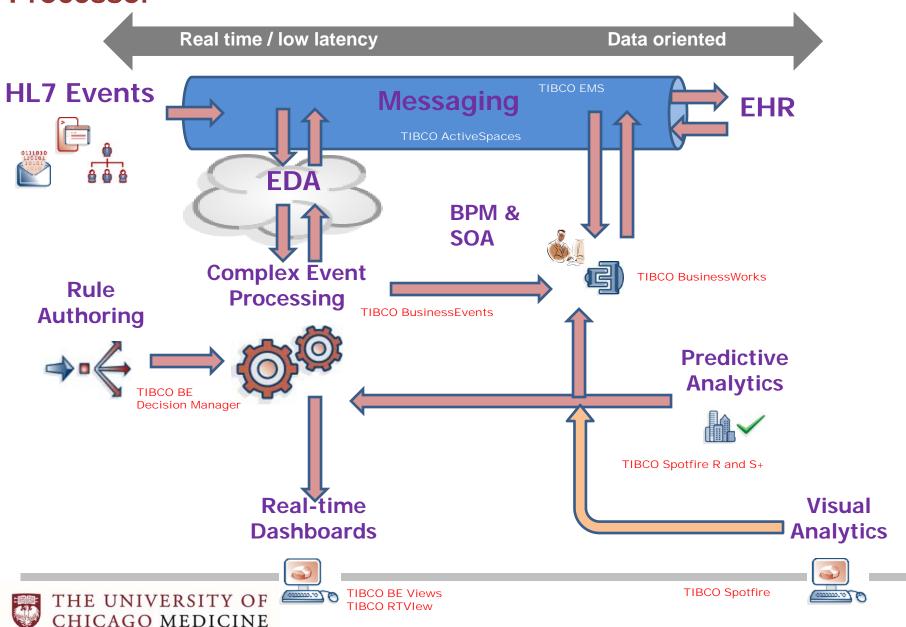
Source : Wikipedia



### **UCM Architecture Target State**



## Service Oriented Architecture and Complex Event Processor



## **Questions**

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## A Green Button?

#### My Patient

A 55 year old female of Vietnamese heritage with known asthma presents to her physician with new onset moderate hypertension

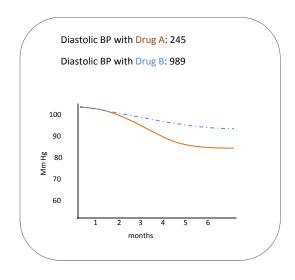
#### Intervention

antihypertensives

#### **Outcome**

Diastolic pressure < 90 mm Hg





Longhurst et al. A 'Green Button' For Using Aggregate Patient Data At The Point Of Care. *Health Affairs*, July 2014.

## **Analytics Panel**

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- Jon Palma, MD, MS and Veena Goel, MD Stanford, CA <u>jpalma@stanfordchildrens.org</u> and <u>vgoel@stanford.edu</u>
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