TRANSLATING DATA IN ANESTHESIA:

AN INTRODUCTION TO PREDICTIVE ANALYTICS

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TRANSLATING DATA

How do we get from blood transfusion to big data?!

Outline:

- ❑Big Data Unraveled
- ❑How is it used in Industry
- ❑What is predictive analytics
- ❑What does it mean in Healthcare
- ❑Why could it be important in anesthesia

BIG DATA → PREDICTIVE ANALYTICS → ANESTHESIA

Big Data Landscape

Vertical Apps
Predictive Policing, bloomreach, MYRRIX

Log Data Apps
splunk>, loggly, sumologic

Ad/Media Apps
rocketfuel, collective[i], bluefin, Recorded Future, LuckySort, Media Science, TURN, DataXu

Business Intelligence
ORACLE | Hyperion, SAP, BusinessObjects, RJMetrics, Microsoft | Business Intelligence, IBM, COGNOS, birst, MicroStrategy, Autonomy, QlikView, bime, DOMO, Chart.io, GoodData

Analytics and Visualization
tableau, Palantir, OPERA, metaLayer, dataspora, METAMARKETS, centrifuge, TERADATA ASTER, sas, TIBCO, KARMASPHERE, panopticon, pentaho, Datameer, platfora, ClearStory, CIRRO, alteryx, visual.ly, AYATA

Data As A Service
factual., kaggle, knoema, GNIP, DATASIFT, Windows Azure Marketplace, INRIX, LexisNexis, Spatial Curve, LOQATE

Analytics Infrastructure
Hortonworks, VERTICA, MAPR, cloudera, INFOBRIGHT, PARACCEL, EMC², GREENPLUM, NETEZZA, kognitio, DATASTAX, EXASOL, calpont

Operational Infrastructure
COUCHBASE, 10gen, TERADATA, HADAPT, TERRACOTTA, VoltDB, MarkLogic, INFORMATICA

Infrastructure As A Service
amazon web services, Windows Azure, infochimps, Google BigQuery

Structured Databases
ORACLE, MySQL, SQL Server, PostgreSQL, IBM DB2, SYBASE, memsql

Technologies
hadoop, hadoop MapReduce, mahout, APACHE HBASE, Cassandra

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WHAT IS

Big data is a buzzword and a "vague term”

In 2000, 25% of stored information in the world was digital, and the remaining 75% was analog, existing on paper, film, photographic prints, vinyl, and so on.

By 2007, 93% of information was digital, and only 7% was analog.

1.8 zettabytes data globally in 2011
1billion gigabytes = 1 exabyte
1000 exabytes =1 zetttabytes

DEFINITIONS

Volume

The quantity of generated and stored data. The size of the data determines the value and potential insight- and whether it can actually be considered big data or not.

Variety

The type and nature of the data. This helps people who analyze it to effectively use the resulting insight.

Velocity

In this context, the speed at which the data is generated and processed to meet the demands and challenges that lie in the path of growth and development.

Variability

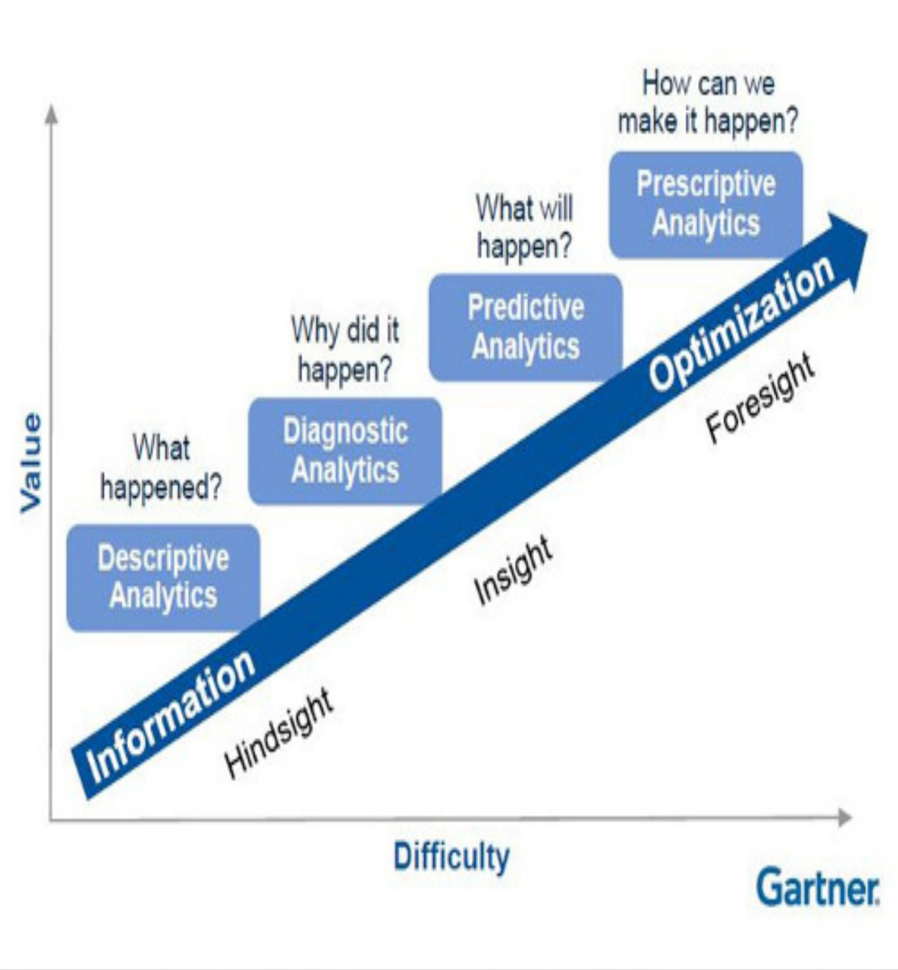
Inconsistency of the data set can hamper processes to handle and manage it.

Veracity

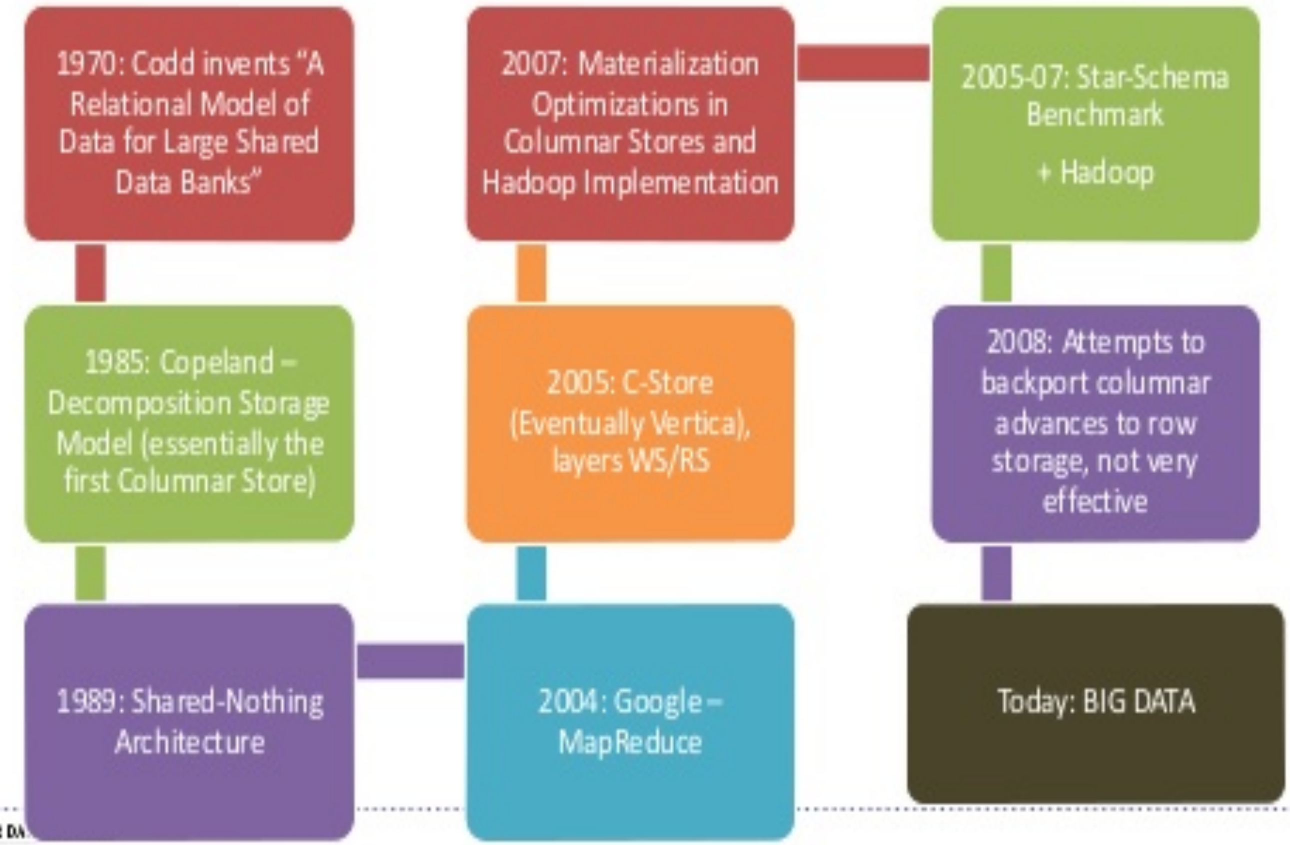
The quality of captured data can vary greatly, affecting accurate analysis.

FOUR TYPES OF BIG DATA (BUSINESS INTELLIGENCE)

- Prescriptive – This type of analysis reveals what actions should be taken.
- Predictive – An analysis of likely scenarios of what might happen (forecasts).
- Diagnostic – A look at past performance to determine what happened and why.
- Descriptive – What is happening now based on incoming data.



A Short History of (Big) Data Technology



Smarter Cities: Turning Big Data Into Insight

City Planning and Operations

$1 Trillion
global annual savings could be attained by optimizing public infrastructure.
Source: McKinsey

$57 Trillion
in infrastructure investments will be needed between 2013-2030.
Source: McKinsey

Transportation Analytics

50 Hours
of traffic delays per year are incurred, on average, by travelers.

30 Billion
people all over the world travel approximately 30 billion miles per year. By 2050, that figure will grow to over 150 billion miles.

Water Management

60%
of water allocated for domestic human use goes to urban cities.

$14 Billion
in potable water is lost every year because of leaks, theft and unbilled usage.
Source: World Bank

Open Cloud

37,000
cloud experts support IBM's industry team alone.

$6 Billion
has been invested by IBM in more than a dozen acquisitions to accelerate its cloud initiatives.

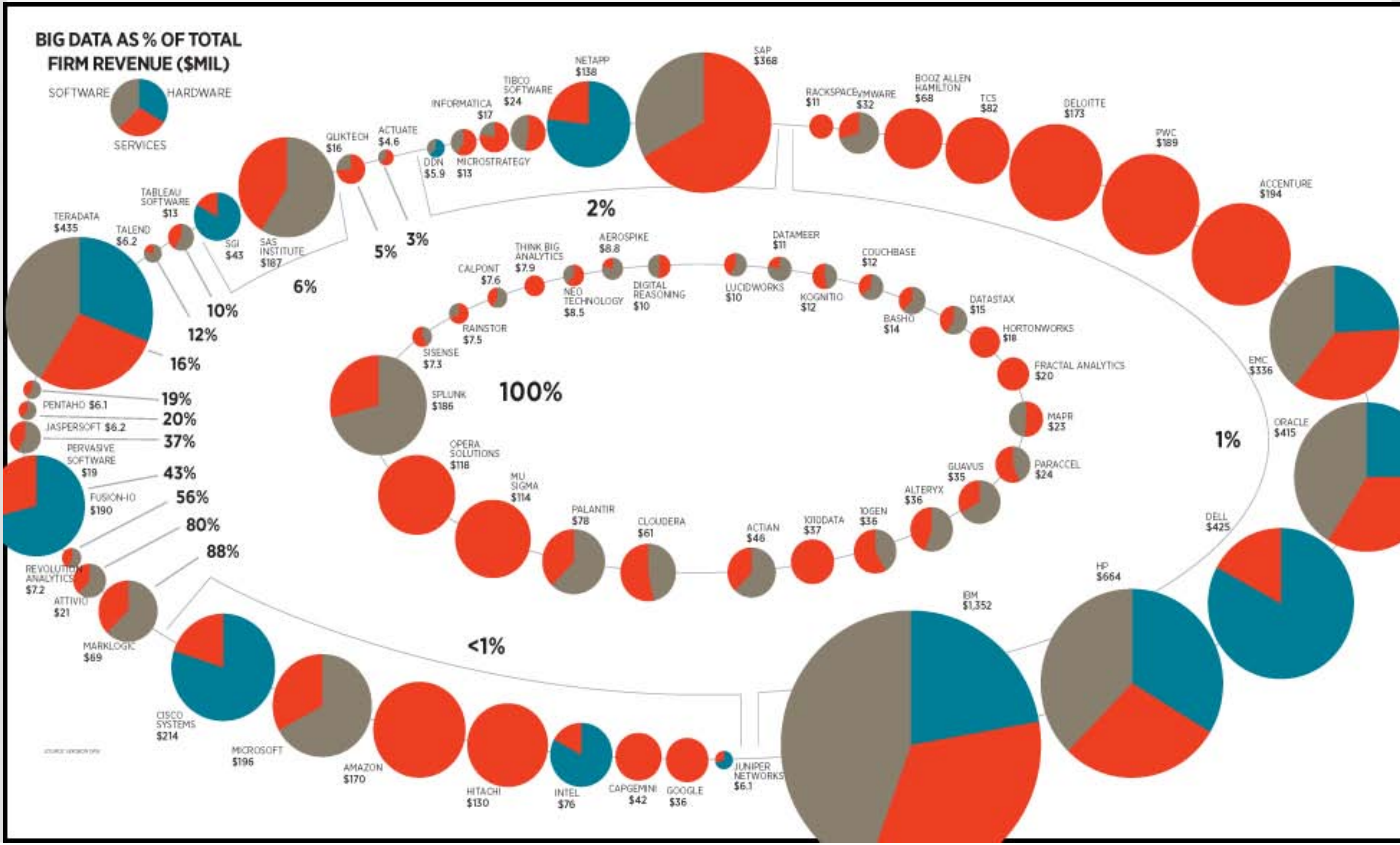
IBM Intelligent Operations software is designed with cities, for cities, to provide the tools to monitor, visualize and analyze vital city services such as water and wastewater systems, transportation, infrastructure planning, permit management and emergency response.

IBM

BIG DATA IS EVERYWHERE

- Actuarial work in life insurance risk
- Casino population risk/pay outs
- Government
  - US National Security Agency and the Utah Data Center
  - US elections in 2012
  - Indian elections in 2014
  - UK's public services, data on prescription drugs
- Manufacturing- improvements in supply planning
- Media- tailoring advertisements
- Retail- Walmart, Target, Macys
- Real Estate- Windmere Real Estate- GPS and driving time
- Banking- FICO detection system
- Sports- Moneyball, Formula One races
- Education
- Healthcare

REVENUE GENERATION



Big data analytics has helped healthcare improve by providing personalized medicine and prescriptive analytics, clinical risk intervention and predictive analytics, waste and care variability reduction, automated external and internal reporting of patient data, standardized medical terms and patient registries and fragmented point solutions.

BIG DATA IN HEALTH CARE

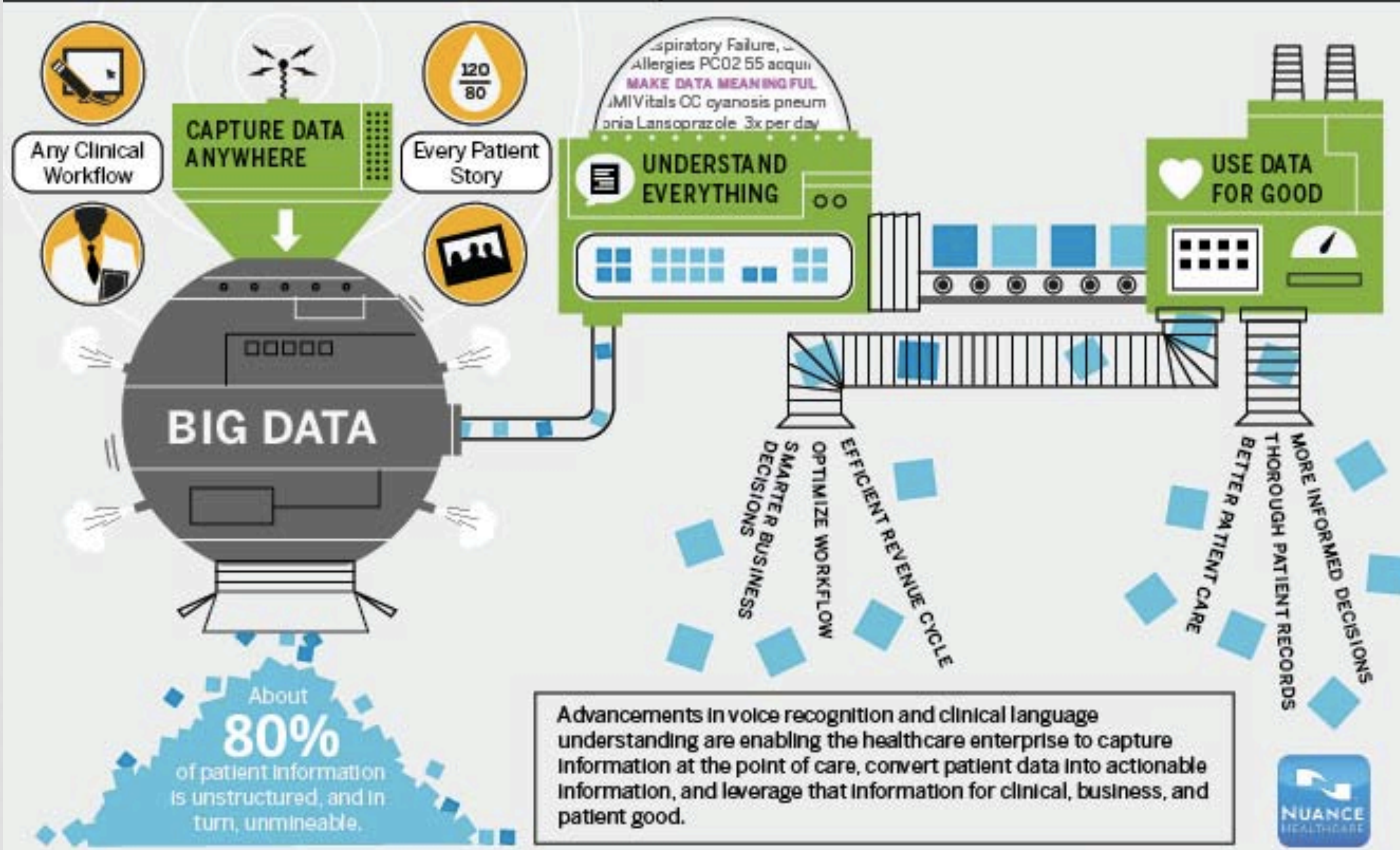
In today's data-driven age, healthcare is transitioning ***from opinion-based decisions <u>to informed decisions</u>*** *based on data and analytics*

- ➢*Rapid expansion of EMRs*
- ➢*Digital and connected technology- MRIs, sensors*

HEALTHCARE'S DATA CONUNDRUM

FROM DISPARATE DATA TO MEANINGFUL INFORMATION

We can empower healthcare organizations, providers and payers to unify the capture, analysis, and use of data to drive smarter care and business.



Advancements in voice recognition and clinical language understanding are enabling the healthcare enterprise to capture information at the point of care, convert patient data into actionable information, and leverage that information for clinical, business, and patient good.

NUANCE HEALTHCARE

www.nuance.com/for-healthcare

Areas to deliver value:

- Clinical operations
- Payment/pricing
- R&D
- New business models
- Public health
- Comparative effectiveness research
- Clinical decision support
- Remote patient monitoring
- Health economics
- Personalized medicine

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Information technology innovation: the power and perils of big data

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- Early detection of diseases/management
- Detection of health-care fraud
- Genomics analytics
- Device/remote-monitoring and patient profile analytics
- Use massive amounts of data *appropriately*
- Perioperative outcomes research- numerous databases
  NSQUIP, MPOG, NACOR
- Data security
- Specialized skills


GETTING
STARTED
WITH
PREDICTIVE
ANALYTICS

WHAT IS PREDICTIVE ANALYTICS?

BIG DATA → PREDICTIVE ANALYTICS

The Fun Stuff: Using Big Data for Predictive Analytics

The use cases for predictive analytics in healthcare have been limited up to the present because we simply haven't had enough data to work with.

Big data can help fill that gap.

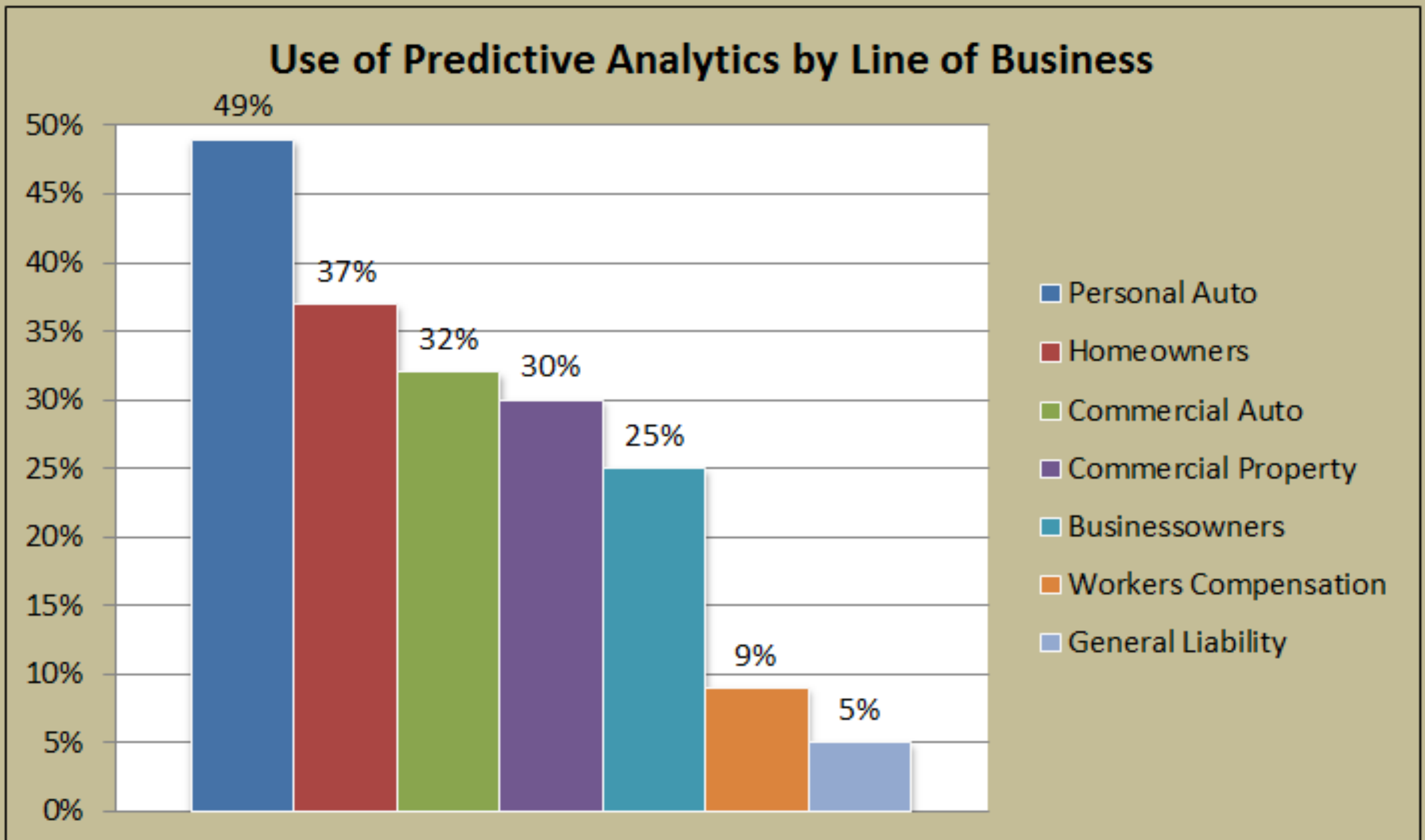
PREDICTIVE ANALYTICS

- A practice of extracting information from existing data sets in order to determine patterns and predict future outcomes and trends
- It does not tell you what will happen in the future. It *forecasts what might happen in the future with an acceptable level of reliability.*

POTENTIAL IMPACT

- Today, health systems' need for data-driven quality and cost improvement is urgent.
- Healthcare organizations cannot afford to wait for big data technology to mature before diving into analytics.
- Must be innovative in our use of medical technologies to drive cost-effective clinical practice

PREDICTIVE ANALYTICS HISTORY



Source: Earnix/ISO September 2013 Survey

VIEWPOINT

INNOVATIONS IN HEALTH CARE DELIVERY

Integrating Predictive Analytics Into High-Value Care

The Dawn of Precision Delivery

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Meetali Kakad, MD, MPH
Department of

United States health care costs are twice as high as spending in most industrialized countries. One key opportunity for health systems to improve value is by limiting overuse of costly resources, in part by focusing these resources toward high-risk patient groups.[1] Some health systems have been using retrospective claims data or other approaches, like the Framingham risk model, to identify high-risk individuals. However, most systems today are doing little in the way of risk stratification, and physicians often find it difficult to apply these characterizations of risk to the care of an individual patient.

els around clinical issues, such as acute intensive care unit decompensation and hospital readmissions.[1]

As organizations like Amazon and American Airlines have shown, however, development of these models is only a first step. Few health systems currently use predictive analytics at scale to influence health care delivery. Health systems must identify strategies to implement predictive risk algorithms into clinical practice.

Using Predictive Analytics to Focus Intensity of Services Across the Care Continuum

- "An opportunity for health systems to improve value by limiting overuse of costly resources"
- EHRs now allowing clinicians and health systems to determine an individual's real time risk of a clinical event
- <u>Precision Delivery</u> involves using an individual's electronic health data to predict risk and personalize care to substantially improve value

KAISER PERMANTE OF NORTHERN CALIFORNIA

- Used maternal health data from 600,000 live births to determine probability of early-onset neonatal sepsis in non-premature infants prior to birth
- data integrated with objective clinical data from the newborn at birth
- Categorized newborns as low, medium, high risk for sepsis prior prior to giving antibiotics
- Decreased use of systemic antibiotics by 30% without harm

Escobar GJ et al. Stratification of risk of early-onset sepsis in newborns $\geq$ 34 weeks gestation. Pediatrics. 2014:133(1):30-36.

PARKLAND HEALTH AND HOSPITAL SYSTEM

- algorithm based on 29 clinical, social, behavioral, and utilization factors available within 24 hours of admission
- prospective study of 228 patients with heart failure to predict readmission
- Targeted evidence-based interventions: follow up phone calls, detailed education, outpatient appointments
- Compared to patients prior to intervention, 26% relative reduction in readmissions

Amarasingham R et al. Allocating scarce resources in real-time to reduce heart failure readmissions: A prospective, controlled study. BMJ Qual Saf. 2013:22(12):998-1005.

VETERANS HEALTH ADMINISTRATION

- created a data warehouse- repository of patient-level data aggregated from across the system
- calculated risk scores based on variables- demographics, VS, lab results
- used by 1200 clinicians across the system
- nurse care managers use these scores to guide services
- Compared practices/services that used the scoring system, 17% reduction in hospitalizations, 27% in ED visits over a 7 month period

Fihn SD, et al. Insights from advanced analytics at the Veterans Health Administration Health Aff (Millwood).2014;33(7): 1203-11

British Journal of Anaesthesia **115** (3): 350–6 (2015)
Advance Access publication 26 January 2015 · doi:10.1093/bja/aeu552

REVIEW ARTICLES

Big data and visual analytics in anaesthesia and health care†

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- Highlights potential use of data
- Visual analytics techniques that are instantaneous
- Available alongside EHR

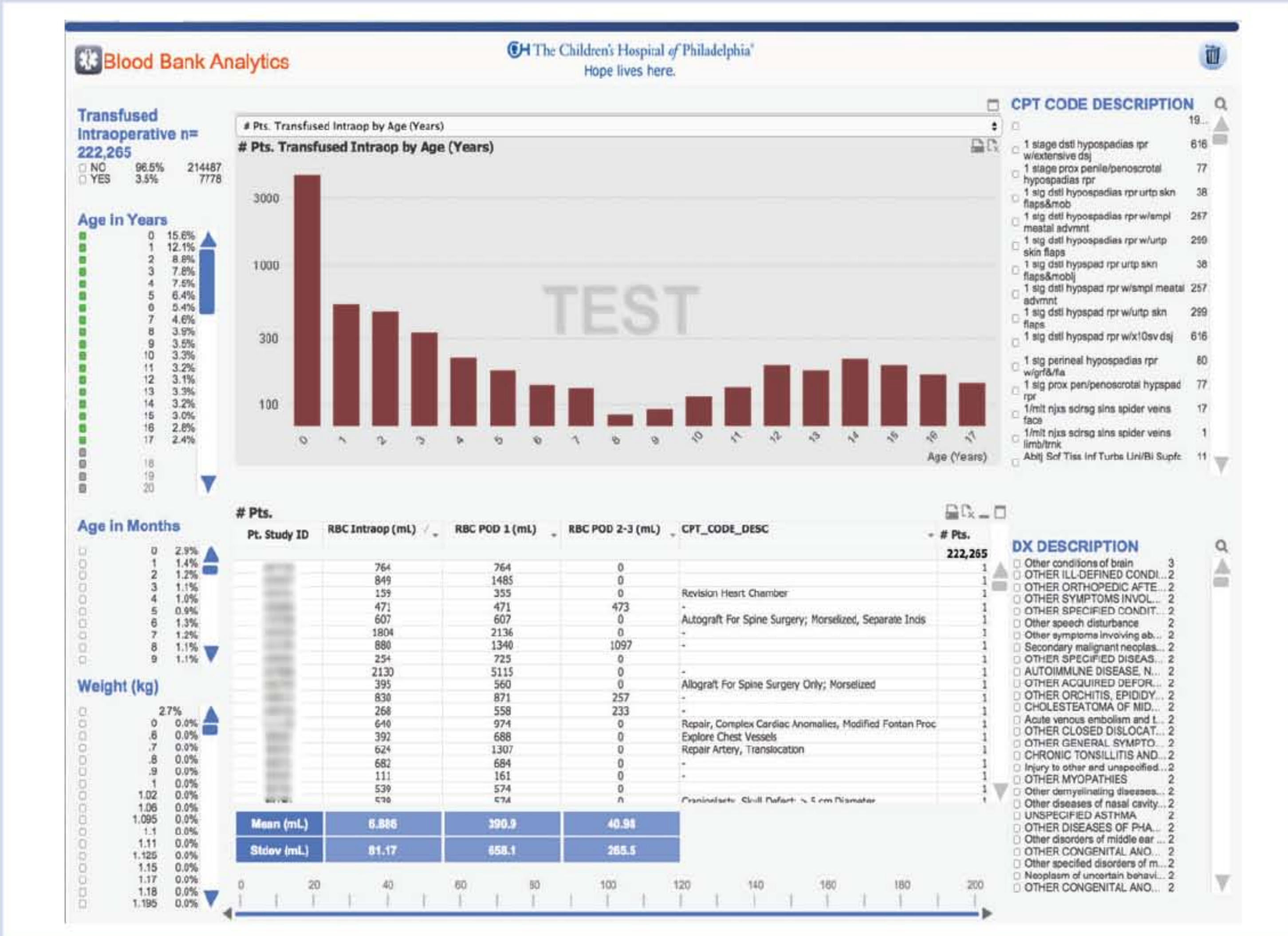


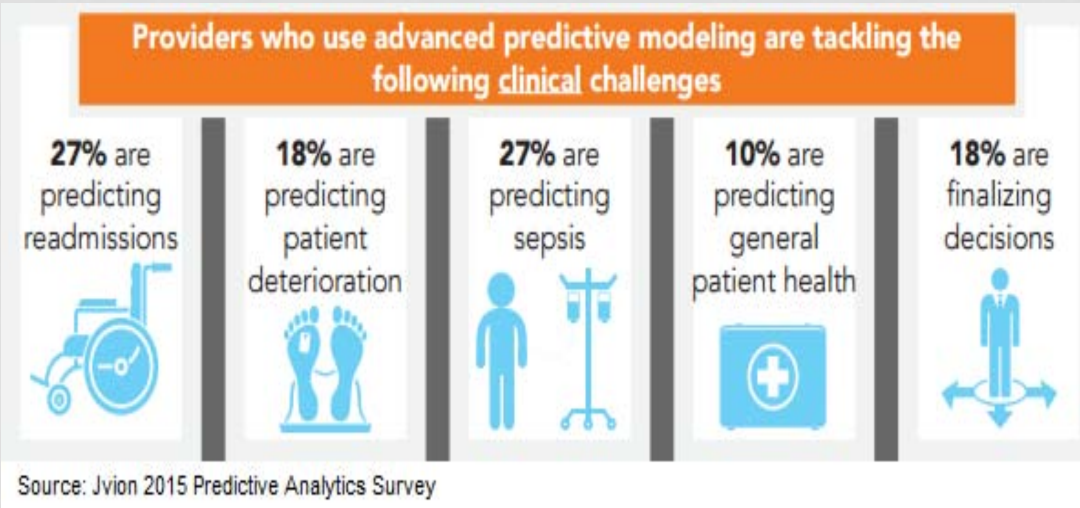
Fig 2 Screen shot of The Children's Hospital of Philadelphia Medication Alert Fatigue visual analytics dashboard. This enables the user to explore electronic health record medication alert data.

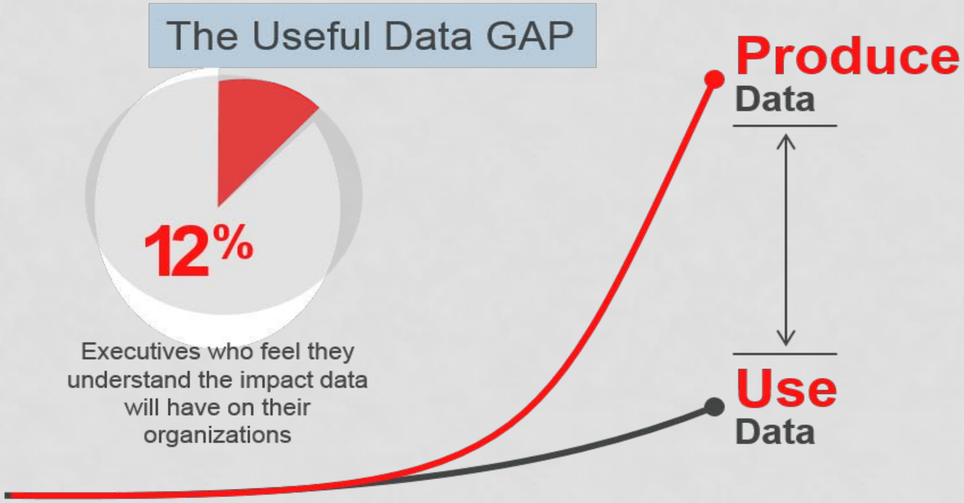
LESSONS FROM INDUSTRY

- Amazon- product recommendation
- American Airlines- ticket pricing trends
- Oakland Athletics- selecting player rosters

Predictive analytics offers an automated means to forecast future health outcomes based on algorithms derived from patient data.

GAP IN POTENTIAL



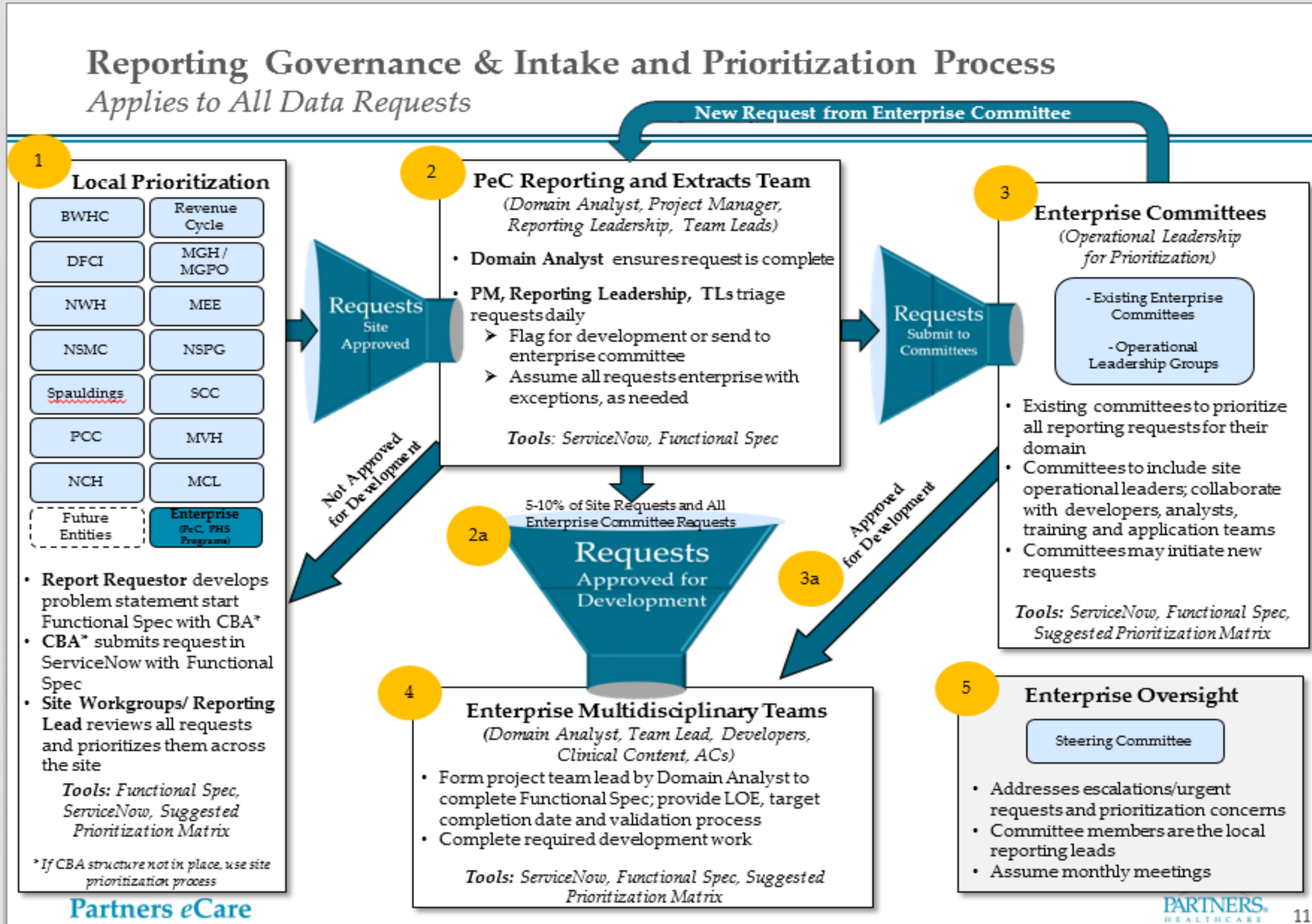


WHAT WE'VE LEARNED SO FAR

- More data does not equate to more insight
- Insight and value are not the same
- DATA + Context = Knowledge
- Ability to interpret data varies based on the data itself
- Implementation itself may prove a challenge

BARRIERS TO BIG DATA IN HEALTHCARE

- Expertise
- Security
- Implementation challenges
- Vast amount of data in text


Reporting Governance & Intake and Prioritization Process
Applies to All Data Requests
New Request from Enterprise Committee
1
Local Prioritization
BWHC
Revenue Cycle
DFCI
MGH / MGPO
NWH
MEE
NSMC
NSPG
Spauldings
SCC
PCC
MVH
NCH
MCL
Future Entities
Enterprise (PeC, PHS Programs)
• Report Requestor develops problem statement start Functional Spec with CBA*
• CBA* submits request in ServiceNow with Functional Spec
• Site Workgroups/ Reporting Lead reviews all requests and prioritizes them across the site
Tools: Functional Spec, ServiceNow, Suggested Prioritization Matrix
* If CBA structure not in place, use site prioritization process
Requests Site Approved
Not Approved for Development
2
PeC Reporting and Extracts Team
(Domain Analyst, Project Manager, Reporting Leadership, Team Leads)
• Domain Analyst ensures request is complete
• PM, Reporting Leadership, TLs triage requests daily
➢ Flag for development or send to enterprise committee
➢ Assume all requests enterprise with exceptions, as needed
Tools: ServiceNow, Functional Spec
Requests Submit to Committees
3
Enterprise Committees
(Operational Leadership for Prioritization)
- Existing Enterprise Committees
- Operational Leadership Groups
• Existing committees to prioritize all reporting requests for their domain
• Committees to include site operational leaders; collaborate with developers, analysts, training and application teams
• Committees may initiate new requests
Tools: ServiceNow, Functional Spec, Suggested Prioritization Matrix
2a
5-10% of Site Requests and All Enterprise Committee Requests
Requests Approved for Development
3a
Approved for Development
4
Enterprise Multidisciplinary Teams
(Domain Analyst, Team Lead, Developers, Clinical Content, ACs)
• Form project team lead by Domain Analyst to complete Functional Spec; provide LOE, target completion date and validation process
• Complete required development work
Tools: ServiceNow, Functional Spec, Suggested Prioritization Matrix
5
Enterprise Oversight
Steering Committee
• Addresses escalations/urgent requests and prioritization concerns
• Committee members are the local reporting leads
• Assume monthly meetings
Partners eCare
PARTNERS HEALTHCARE
11

CRITIQUES

- To overcome this insight deficit, must be complemented by "big judgment," according to an article in the Harvard Business Review.
- If the systems dynamics of the future change (if it is not a stationary process), the past can say little about the future.
- Conventional scientific approaches are based on experimentation.
- Multiple comparisons problem: simultaneously testing a large set of hypotheses is likely to produce many false results that mistakenly appear significant.

FALSE POSITIVES

- Google Flu Trends failed to deliver good predictions in recent years, overstating the flu outbreaks by a factor of two.
- Academy awards and election predictions solely based on Twitter were more often off than on target.
- Google Translate—which is based on big data statistical analysis of text—does a good job at translating web pages. However, results from specialized domains are skewed.
- 2016 U.S. Presidential Elections- Forbes predicted "If you believe in *Big Data* analytics, it's time to begin planning for a Hillary Clinton presidency and all that entails." *(Markman, Jon. "Big Data And The 2016 Election". Forbes. Retrieved 2016-11-27.)*

CRITIQUES *ESPECIALLY IN HEALTHCARE*

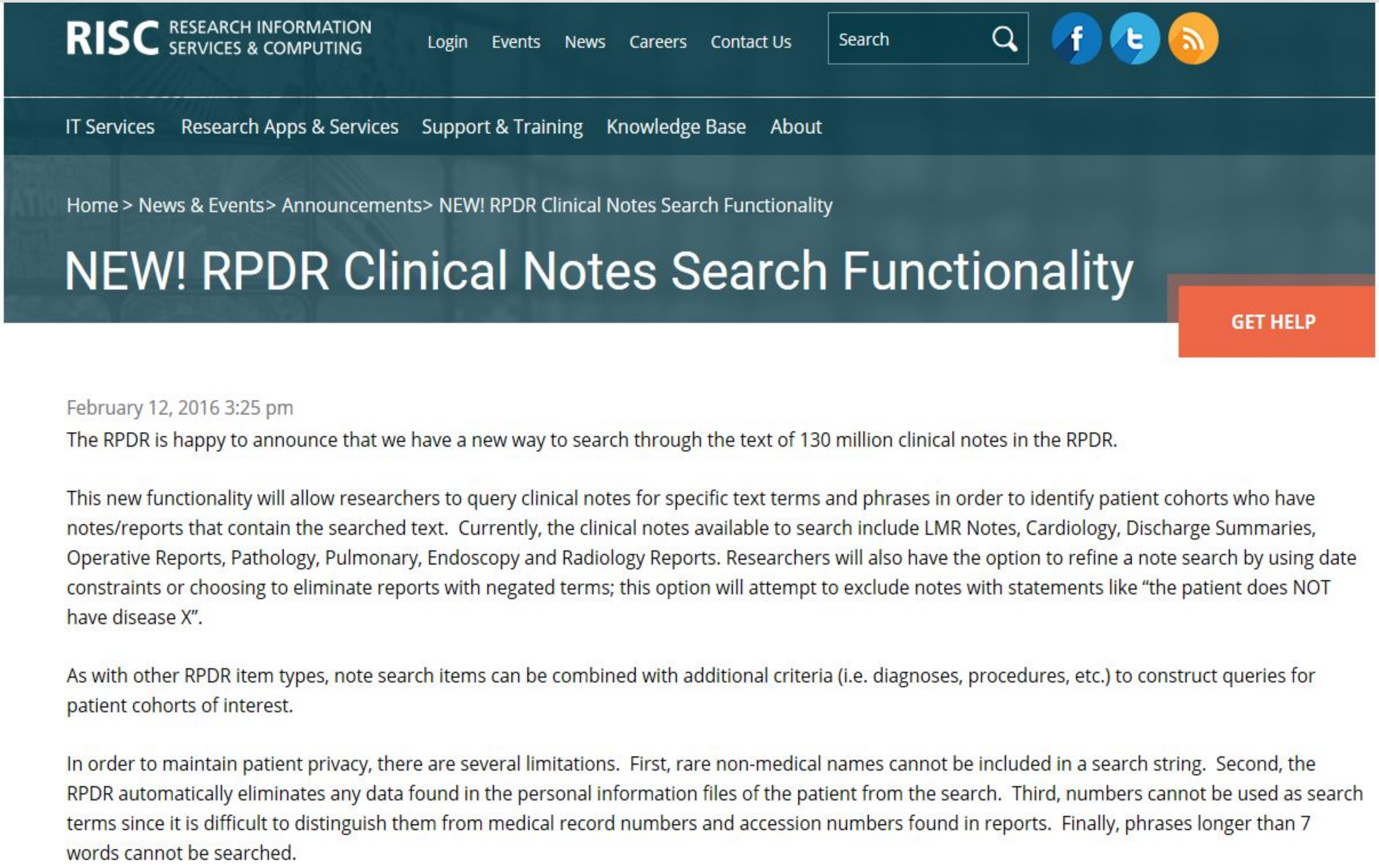
Privacy advocates are concerned about the threat to privacy represented by increasing storage and integration of personally identifiable information; expert panels have released various policy recommendations to conform practice to expectations of privacy.

- What of decreased role of clinicians
- Lack of training

WHAT DOES SUCCESS LOOK LIKE?

- Integration is as important
- Infrastructure
- Algorithms outputs need to be actionable- prompt pre-specified, evidence-based activities
- Flexibility- need to quickly adjust for real-time data to allow iteration

PARTNERS/ MGH



MGH AND CODMAN CENTER FOR CANCER RESEARCH

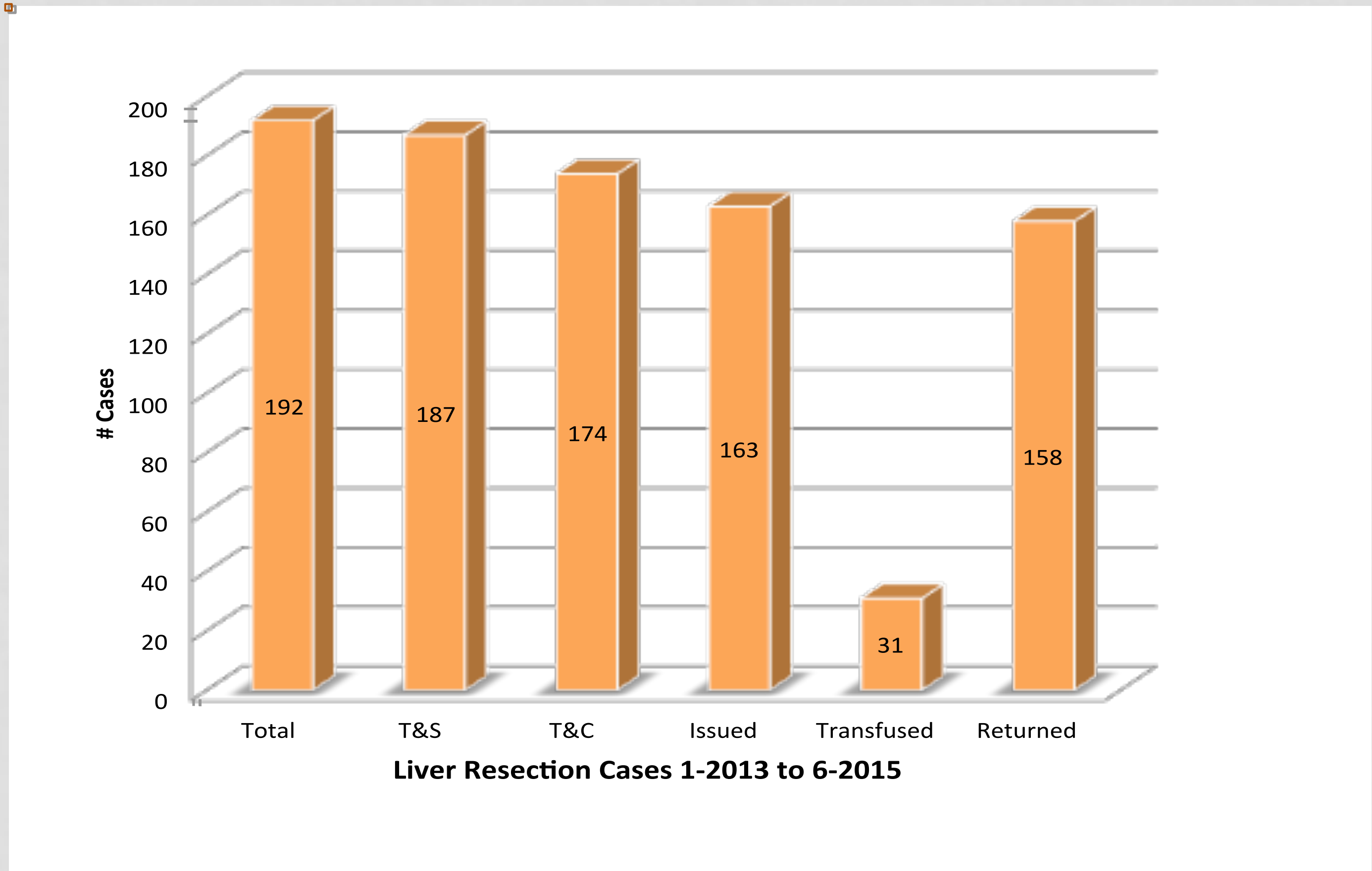
- Spring 2016 Grand Rounds for Surgery
- Collaboration with David Chang, PhD, Director of Healthcare Policy and Research
- How to use analytics
- Narrowing the scope- surgery specific?
- Developing a risk score or a type of check list
- Using a larger database for better power

OBJECTIVE

- To develop a <u>clinically useable</u> checklist (one that can be done quickly at bedside without complex calculators) to reduce blood waste using a national database
  - Willing to sacrifice some statistical precision in order to make a tool that is clinically useable
  - Goal is to make this an adjunctive tool, not a hard protocol, and so precision is unnecessary

Statistical analysis credited to Dr Chang and the Codman team.

DATA: LIVER RESECTION COUNTS (2013-15)



T&S ordered	T&C ordered	Issued	Transfused
97%	91%	84%	16%

METHODS

- ACS- NSQIP database
  - Developed using 2010-2013 data
  - Validated using 2014 data

- Population: Hepatectomy patients

  CPT: 47120 - Partial lobectomy
  47122 -Trisegmentectomy
  47125 - Total left lobectomy
  47130 - Total right lobectomy

ENDPOINT

- Occurrences of bleeding transfusion: "At least 1 unit of packed or whole red blood cells given from the surgical start time up to and including 72 hours postoperatively"

COVARIATES

- **Pre-op comorbidities**: ascites, bleeding disorders, congestive heart failure (CHF) in 30 days before surgery, disseminated cancer, diabetes mellitus with oral agents or insulin, dyspnea, functional health status prior to surgery, hypertension requiring medication, systemic sepsis , steroid use for chronic condition, severe COPD history, ventilator dependent, >10% loss body weight in last 6 months, smoker within one year

- **Pre lab**: total bilirubin, BUN, hematocrit, dialysis, serum sodium, acute renal failure, SGOT, platelet count, albumin, transfusion, WBC, alkaline phosphatase, serum creatinine

- **Surgery-related**: CPT (Partial, total left, total right lobectomy, Trisegmentectomy), emergency surgery, ASA, surgical specialty, transfer status

(Chemotherapy for malignancy in <= 30 days pre-op and race are not included due to large numbers of missing data.)

RESULTS

- Total patients: 15,551
  - 11,236 (72.25%) is used for development group
  - 4,315 (27.75%) is used for validation group
- Average age: 58.7 yr
- Gender: 8,062 (51.89%) Female
- Surgical type:
  - 9,654 (52.08 %) Partial lobectomy (CPT 47120)
  - 2,930 (18.84%) Total right lobectomy (CPT 47130)
  - 1,583 (10.18%) Total left lobectomy (CPT 47125)
  - 1,384 (8.90%) Trisegmentectomy (CPT 47122)
- Transfusion rate: 3,527 (22.68%)

Generate index scores

Variables	OR 1 (stepwise selection)	OR 2 (regression excluding low-frequency variables)	OR 2/1.16	Round (Index score 1)
wbc_less4point5	1.16	1.16	1.00	1
asa_cat3	1.42	1.47	1.26	1
asa_cat4	2.34	2.56	2.20	2
cpt_47122	2.36	2.32	2.00	2
cpt_47125	1.33	1.28	1.10	1
cpt_47130	2.11	2.09	1.80	2
prehct_lessthan38	2.64	2.78	2.40	2
preplt_less150	1.16	1.20	1.03	1
prehct_38_45	1.40	1.39	1.20	1
wbc_gt10	1.23	1.35	1.16	1
presgot_40	1.18	1.21	1.04	1
bmi_gt35	1.21	1.23	1.06	1
preplt_gt400	1.79	1.76	1.52	2
precreat_1point2	1.29	1.33	1.15	1
Prealbumless3	1.27	1.30	1.12	1
prealkph_125	1.42	1.42	1.23	1
prebili_1	1.16	1.17	1.01	1
Total #	10511	10836		10836
Discrimination				
ROC	0.7054	0.6979		0.6856
Goodness-of-fit				
Pearson χ^2	2645.11	2054.01		12.72
P-value	0.4410	0.5700		0.3900
Pseudo r2	0.0928	0.0850		0.0758

DATA VALIDATION

	Development group (2010-2013 data)	Validation group (2014 data)
Sample size (Patients)	10,836	4,158
Discrimination		
ROC	0.6856	0.6974
Goodness-of-fit		
Pearson $\chi 2$	12.72	14.18
P-value	0.3900	0.2892
Pseudo r2	0.0758	0.0830

- The goodness-of-fit tests fail to reject the null hypothesis for both the development group and the validation group, indicating the model fits our data.

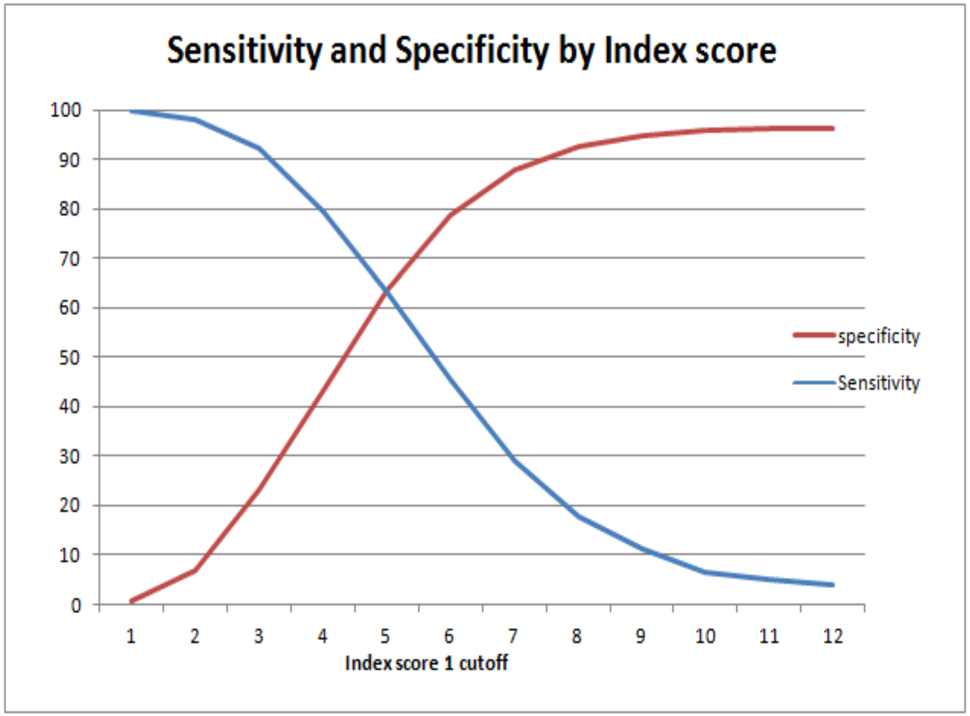
CHECKLIST

Items (& points)			Checkbox
CPT	Total left lobectomy	(1 point)	
	Trisegmentectomy	(2 points)	
	Total right lobectomy	(2 points)	
ASA	3-Severe Disturb	(1 point)	
	4-Life Threat/5-Moribund	(2 points)	
BMI	>35	(1 point)	
WBC	<=4.5 or >10	(1 point)	
Preop hematocrit	<=38	(2 points)	
	38-45	(1 point)	
Preop platelet	<=150	(1 point)	
	>400	(2 points)	
Preop creatinine	>=1.2	(1 point)	
Preop albumin	<3	(1 point)	
Preop SGOT	>=40	(1 point)	
Preop alk phos	>=125	(1 point)	
Preop bili	>=1	(1 point)	

HOW TO USE IT?

- Action is binary
- Without a cutpoint analysis, people may end up choosing different thresholds for actions arbitrarily, defeating the purpose of data-driven approach
  - e.g., debate about GCS 14 vs. 13 for admission
- But will lead to risk-benefit trade-offs

Sensitivity & Specificity (Trade-off)

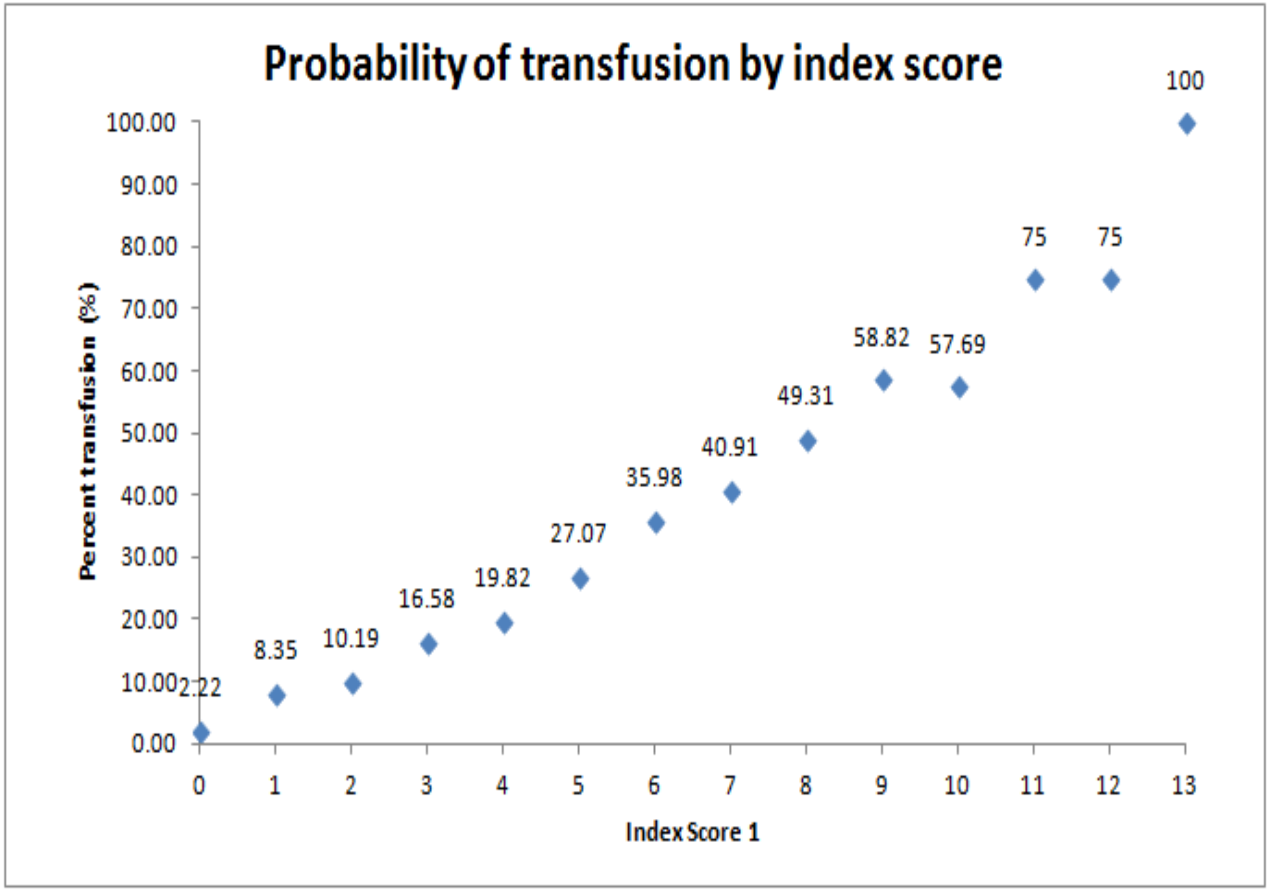


Index score 1 cutoff	Sensitivity	specificity	The sums
1	99.96	0.51	100.47
2	98.13	6.8	104.93
3	92.22	23.05	115.27
4	79.42	43.15	122.57
5	63.34	63.46	126.8
6	45.27	78.65	123.92
7	28.84	87.77	116.61
8	17.73	92.78	110.51
9	11.07	94.92	105.99
10	6.58	95.9	102.48
11	4.9	96.29	101.19
12	3.78	96.4	100.18

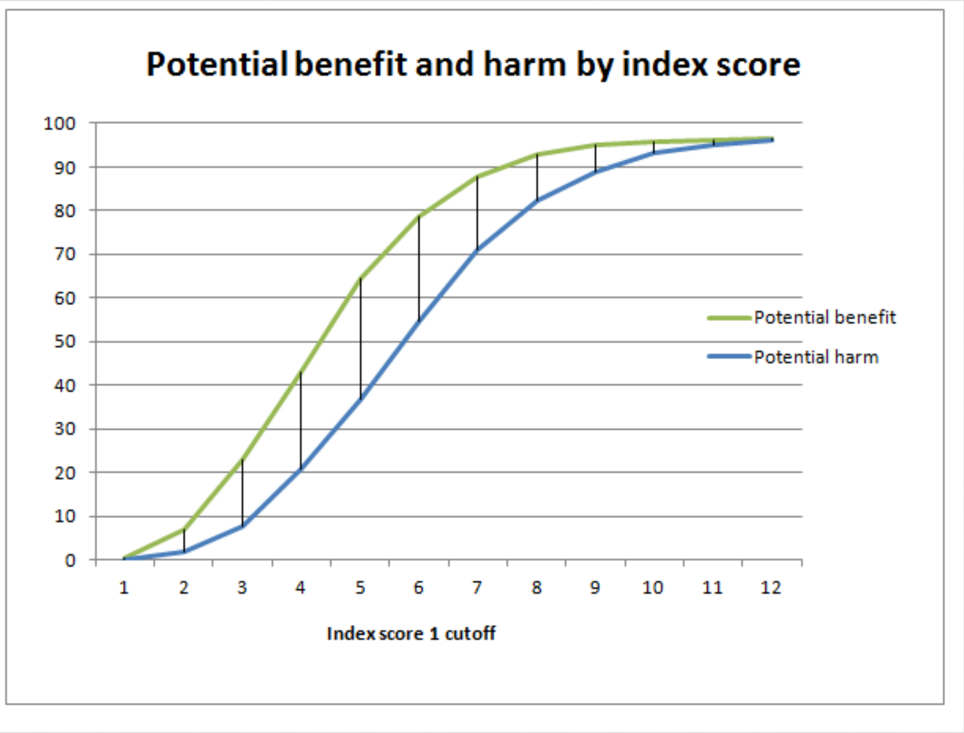
IMPACT

- Potential benefit: Blood saved by not pre ordering it for those who do not need it.
  - Assumption: Blood is being ordered on 100% of patients
- Potential harm: Patients who needed blood but did not have it pre -ordered before surgery

Blood Transfusion Rate by Index Score



Potential Benefit & Potential Harm



Index score 1 cutoff	Potential benefit	Potential harm	The differences
1	0.51	0.04	0.47
2	6.8	1.87	4.93
3	23.05	7.78	15.27
4	43.15	20.58	22.57
5	64.46	36.66	27.8
6	78.65	54.73	23.92
7	87.77	71.16	16.61
8	92.78	82.27	10.51
9	94.92	88.93	5.99
10	95.9	93.42	2.48
11	96.29	95.1	1.19
12	96.4	96.22	0.18

LIMITATION

- Transfusion not limited to intra-op, includes some post-op as well
  - Over estimates rates of transfusion, which means we may be over-ordering blood based on this tool
  - Nevertheless, we are still saving blood (64% in hepatectomy cases)
  - We could save more blood if we could isolate intra-op transfusion only
    - Can do a single-institutional study, but may not have enough sample size

LIMITATION

- c-statistics not optimal
  - But still better than just consider the procedure in the decision making (ROC=0.5980 (procedure alone) vs ROC= 0.6856 (our model))
- Number of items on the scale may still be too many to be useful clinically

CONCLUSION

- A potentially user-friendly scale that can assist in decision about pre-ordering blood for hepatectomy cases
  - May create a reminder to appear if a hepatectomy patient scores <5 on this scale, to recommend NOT pre-ordering blood
- May reduce blood pre-ordering by 64%
  - May under-order blood for 37% of patients who need it, but there may be no "harm" if blood can be ordered quickly

POTENTIAL IMPACT & CHALLENGES

- *Evidence-based, prescriptive analytics*
  "Translate outcome of analysis into meaningful use"
- *Decrease over-use of blood*
- *Decrease over preparation*
- *Clinical decision tool*
- ***Integration***
- ***Slow adoption***
- ***Scale***

WHY NOW?

- Surge of data demand models
- Leverage data collected to improve care
- Need for high value delivery & Quality indicators
- Give HCO's a competitive advantage
- Need more risk stratification and tools for clinicians

Those organizations adapt these tools may do better both clinically and financially.

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