Harnessing the Power of Data (Big and Small) to Improve Clinical and Economic Outcomes

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Questions for Discussion

- What is Data?
- Who “owns” data in an organization?
- How are data analyzed, trended, reported?
- Who validates data?

Big Data: What is it?

- Vast quantities of data - created by mass adoption of digital technologies – too large or too complex for traditional technology to make sense of it. (McCormick, 2013).
- Lots of diverse data elements coming into the organization at the speed of light.
- The intersection of data and how we use technology to analyze and understand it.
- Simply having ***more*** of the same data doesn't make it "big data"

Big Data: The 3-V's and Beyond

- Volume
- Variety
  - Diversity
- Velocity
  - The speed at which data accumulates
- **Variability**
- **Veracity**
- **Complexity**

The Big Data Revolution

- Vastly increased supply of information
  - Pharmaceutical industry – aggregated research
  - Digitized patient records
- Governmental databases
  - Clinical trials data
  - Insurance data – public programs
- Technological advances provide easy access to multiple sources of information:
  - Payors
  - Hospitals
  - Laboratories
  - Physician offices

Kayyali, Knott, & Van Kuiken, 2013

The Rise of Big Data in Healthcare

- Widespread uptake of EHRs
  - Adoption rates doubling from 2009-2011
  - Federal mandate – HITECH Meaningful Use
- Available data types:
  - Quantitative
  - Qualitative (eg, text based documents, demographics)
  - Transactional data (eg, record of medication delivery)
- Percent of total data used is still relatively small
  - Data seen as a byproduct rather than an asset.

Murdoch & Detsky, 2013

Big Data: Who Benefits?

- Health plans
- Purchasers
- Providers
- ***Patients***

Big Data vs. Small Data

- No hard limit to differentiate small data from big data.
- Big data often made up of multiple small data sets in aggregate.
- Rather than focus on the dividing line between ***big*** and ***small***, one should seek to clarify what insights we hope to gain.
  - Clarifying intent will provide direction
- Small data can have a ***big*** effect.

Big Data: Pros

- Powerful concept
- Used to glean insights and draw conclusions that are often unexpected.
- Able to manage disparate data sources
- Unlimited potential

Big Data: Cons

- Expensive
- Lack of expertise to understand, manipulate, and get valid insights from big data sets.
- Data Scientists
  - PhD level thinkers with significant expertise
  - Hard to come by
- Potential to draw inaccurate conclusions (even with accurate data.
- ***In the hands of the average person, Big Data is dangerous!***

A Guide to User-Centered Healthcare Software and Development. Retrieved from: www.macadamian.com

Big Data: To what end?

- "Most of the data collected by EMRs is largely recreational"
- Number of data points actually used represents only a fraction of those captured by the EMR.
  - Estimated at 400-600 tables out of 1000s available

Small Data

- Local data sets
- Most health systems can function well without Big Data.
- Reporting and analytics needs can usually be met with small data sets.

More Data, More Problems

- Is Big Data Always Right? (Zolden, n.d.)
  - Problems:
    - Vast quantity
    - Disorganized
    - Biased
    - Missing context
    - Signal errors
    - Balance in “lag time”
      - Quick to react and make judgements

https://goo.gl/images/kAEkUa

Information Overload

- Factors leading to information overload (Sittending & Broome, 2015):
  - Failure to process data
  - Processing data incorrectly
  - Delay in processing
  - Acceptance of low quality data
  - Giving up the search for other information

Data Analytics and Decision Making

- Mountains of raw health care data continue to grow.
- Tremendous opportunity to turn data into information
  - Information should be scalable and actionable

Actionable Data

- Data analysis to reveal trends should provide actionable information:
  - Ex: Clinical Risk Prediction Model
    - RDW was strongly correlated with a multitude of clinical events (readmission, falls, infections, pressure ulcers)
  - Results were statistically significant
  - No clinical indication as to why this was significant
  - No clue what to do with this information.
  - Was this “cause and effect”?

The Challenge . . . .

- Clarifying the question
  - “what is the problem we are trying to solve?”
- Answering this questions will lead you to the solution.
  - Big Data need
  - Small Data need

Finding Balance

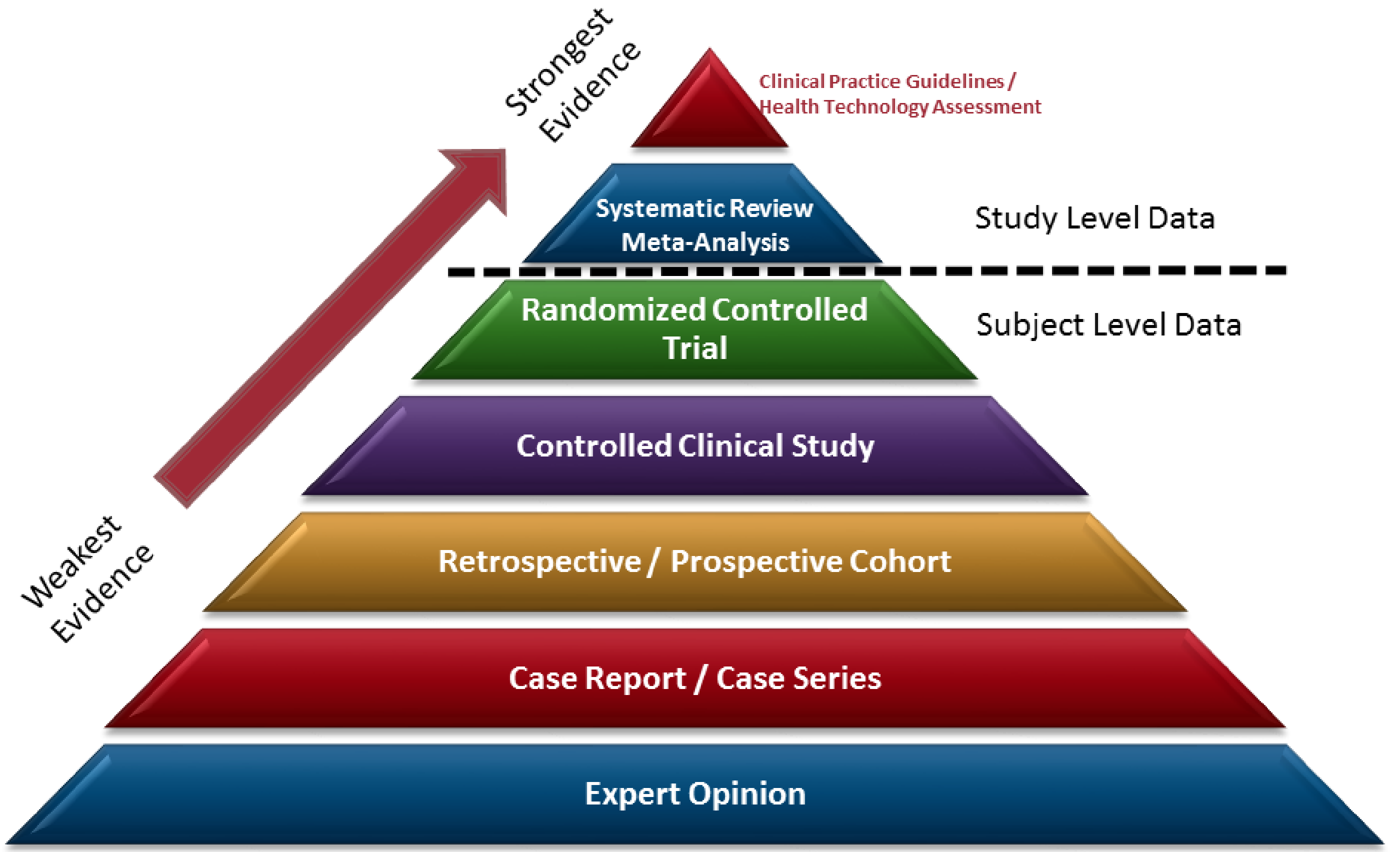
- Recognizing our limitations
  - Big data vs. Small data
  - Anecdotal evidence

Creating a Value Framework

- Right Living
- Right Care
  - Supported by evidence
- Right Provider
- Right Value
  - Value is represented as an equation where
    - **Value = $\dfrac{\textbf{Quality}}{\textbf{Cost}}$**
- Right Innovation

Strength of Evidence

- Pyramid of Evidence

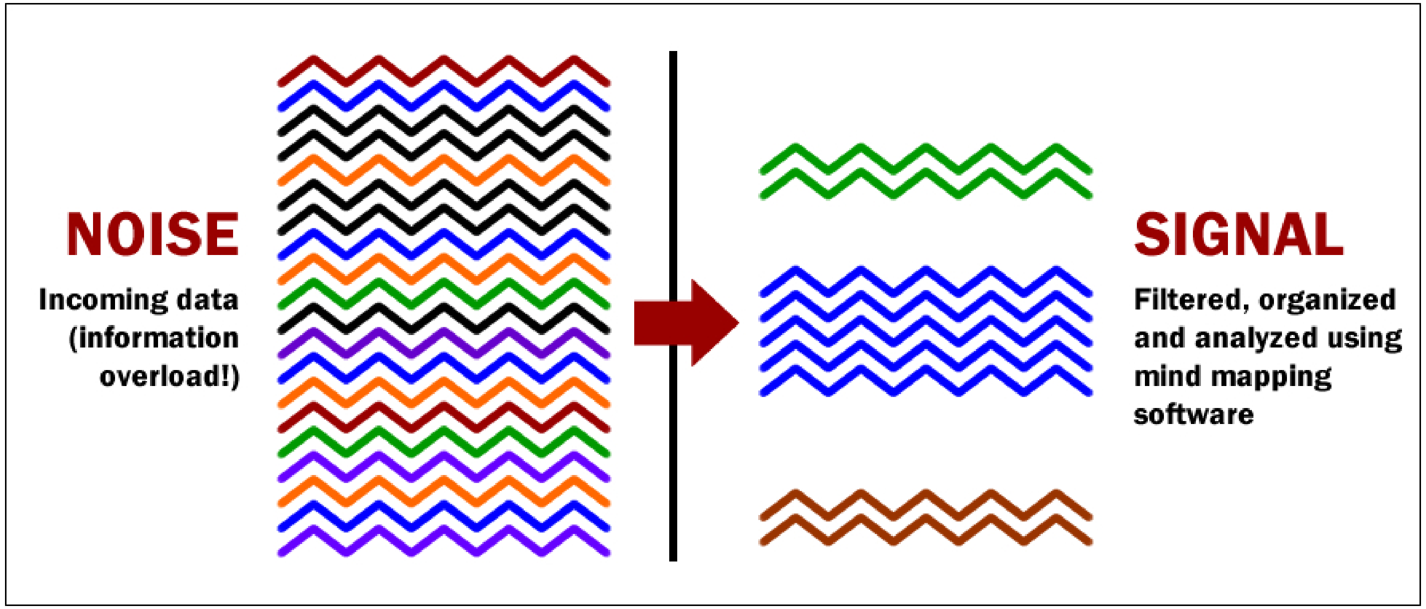


Data Driven Clinical Improvement Decisions

- What are current data sources?
- How are data collected?
- How are data disseminated?
- How are improvement opportunities identified?
  - Examples: NV-HAP, SSI, CAUTI, CLABSI, VAE

Signal vs. Noise

- The challenge for clinicians is to separate the signal from the noise and ensure that we continue to track the signal.



Developing Leader Competencies for Big Data

- Communication and relationship building
  - Collaborative relationship management with key stakeholders
- Knowledge of the healthcare environment
  - Prerequisite to meaningful utilization of big data
- Leadership
  - Systems thinking across organization and continuum of care
- Professionalism
  - This includes opportunities for raising ethical issues or concerns and a forum for discussion and problem solving.
- Business skills
  - Leaders must be able to project the care needs of the industry, as well as communities served

Carr, 2017

Preconditions to Data Driven Therapies

- Valid Data
  - Data hygiene
    - Ensuring data is accurate
    - Everyone’s responsibility
- Contemporary Data
  - We can’t respond to current problems with outdated data

Case Study

- CLABSI Rates at all time low for in institution
- Organizational push to further decrease infection rates.
- Rapid cycle review of data with frequent changes to the "bundle"
- Staff feel disconnected and are unable to differentiate signal from noise.
- Practice begins to vary
- Compliance decreases
- Infections increase
- **Leaders blame staff**
  - Rapid fire education follows

Blaming and Training

- Leaders take ***action***
  - False sense of security
- Doesn’t change clinical practice
- Fails to appreciate the root cause of adverse events
- Negative impact on morale and staff engagement

Case Study (cont)

- Given the amount of attention placed in infection prevention, why did rates worsen?
- What data points were important to measure/monitor?
- When should bundles be modified?

Using Data to Create / Support Clinical Risk Prediction Models

- Problem
  - Hospital readmission rates topped the national healthcare agenda after studies demonstrated that one in five Medicare beneficiaries who received inpatient hospital care were readmitted within 30 days of discharge with an estimated cost to the Medicare program of $17.4 billion in a single year (Black, 2014; Lawrence, 2009).
  - In response to these data, the Centers for Medicare and Medicaid Services (CMS) implemented the Hospital Readmissions Reduction Program as mandated by the Affordable Care Act,
    - Effective in October of 2012.
    - Payments to hospitals with higher-than-expected readmission rates were reduced up to one percent in the first year with an increase to three percent by the year 2015 (American Hospital Association, 2014)

Clinical Problem

- The PICO Question:
  - In hospitalized adult surgical patients, (P) can the LACE assessment tool be used (I) compared to non-stratified discharge preparation (C) to accurately predict patients at risk of unplanned readmission within 30-days of discharge from an index admission (O) within six months of implementation (T)?

Data Validation

- Data were obtained from the hospital administrative database
    - Retrospective sample of all index admissions from the previous five year period (calendar years 2010-2014).
    - A total of 328,920 unique patient admissions were identified from the initial data set.
    - Three patients had missing data fields disqualifying them from analysis.
    - 22,531 experienced a readmission within 30 days following discharge from an index admission
    - This equates with a 7% readmission rate for all patient types in the initial data set.

Intervention

- LACE Index for prediction of 30-day readmission
  - Length of Stay
  - Acuity
  - Co-morbidities
  - ED visits

Assessing Model Performance

Receiver Operator Characteristics Curve – LACE Score				
			Asymptotic 95% Confidence Interval	
Area	Std. Error[a]	Sig.[b]	Lower Bound	Upper Bound
.759	.001	.000	.757	.762

Focus on Outcomes

Readmission Rates for Elective Surgical Cases

	# of Patients Readmitted	# of Patients Not Readmitted	Totals Encounters	Readmission Rates
Time Period #1 (December 2014 – May 2015)	285	2,511	2,796	10.20%
Time Period #2 (June 2015 – November 2015)	223	2,367	2,590	8.60%

Big Data Trends for 2017

- Stronger administration of data security permissions
- In-depth business evaluation of Big Data Projects
  - What is the ROI?
- Immediately gratifying analytics
  - Movement away from batch analytics to immediately actionable data

Data-Driven: Bleeding Edge or Passe'?

- Data is raw material
  - A robust data infrastructure is essential
- Information is a tangible, and actionable ***asset***.
  - Population health
  - Patient-generated data
  - Value-based care
  - Precision Medicine
  - To be determined???

Sullivan, 2017

A New Ethical Imperative?

- Evidence – we are called to provide the highest level of evidence available to us (within our resources). This means we can no longer just rely on anecdotal evidence or small tests of change (single patient case studies).
  - We must become skilled in the art of data analytics to inform practice decisions.
  - We must guard against data overload
  - We must always keep the signal as our focus.

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Thank-You!

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