

Technology Changing Healthcare

EHIN

10 Nov 2015

Alan Stein, MD PhD, Practice Lead – Health & Life Sciences, Big Data SW

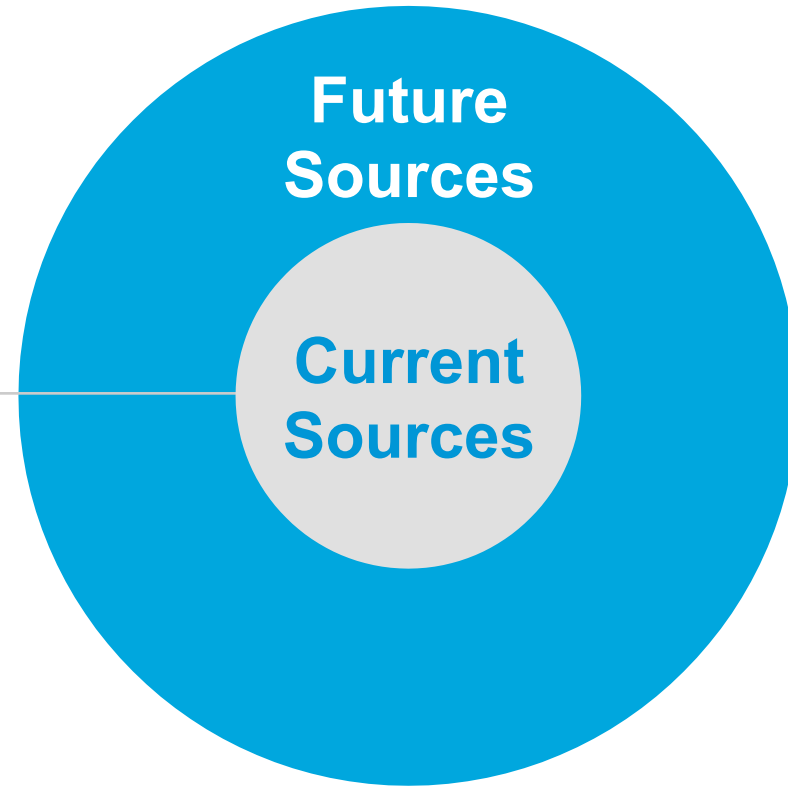
Data is the lifeblood of any health system



Current and Future Healthcare Data

- Revenue management
- Claims
- EMRs
- ICD 9-10
- Genetic Sequences
- Lab values
- Medication records
- Clinician/caretaker notes
- Radiology reports
- Pathology readings
- Clinical quality measures

• Population health data
Traditional healthcare data can be *structured* or *free-text*, and *limited* or *voluminous* in nature



- Video
- Biometrics
- Geotracking
- SMS
- Web chat
- Physiologic monitoring
- Social networks
- Mobile apps
- Sensors
- Survey response
- Biochemical Assays

Nontraditional healthcare data will challenge current methods of *data capture* and *analytics*

We want to turn data into information

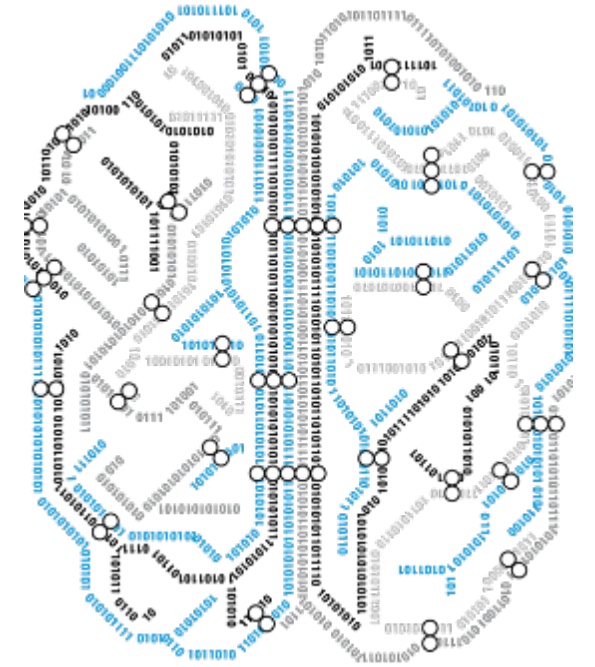
Sample HC Analytics questions

- What are the top 5 reasons for a high-frequency ER visitor? How does this vary for patients that live alone vs those that live with family?
- What percentage of primary Type 1 diabetes care pediatric patients were on an insulin pump in the last calendar year?
- What is the incidence of Pressure Sores / Bed-Hour?
- In the last 30 days, how many patient events Involving Rapid Response or Crash Team occurred? What hospital units were involved?
- How does a missed cardiology follow-up appointment affect the likelihood of a hospitalisation within the next 30 days?



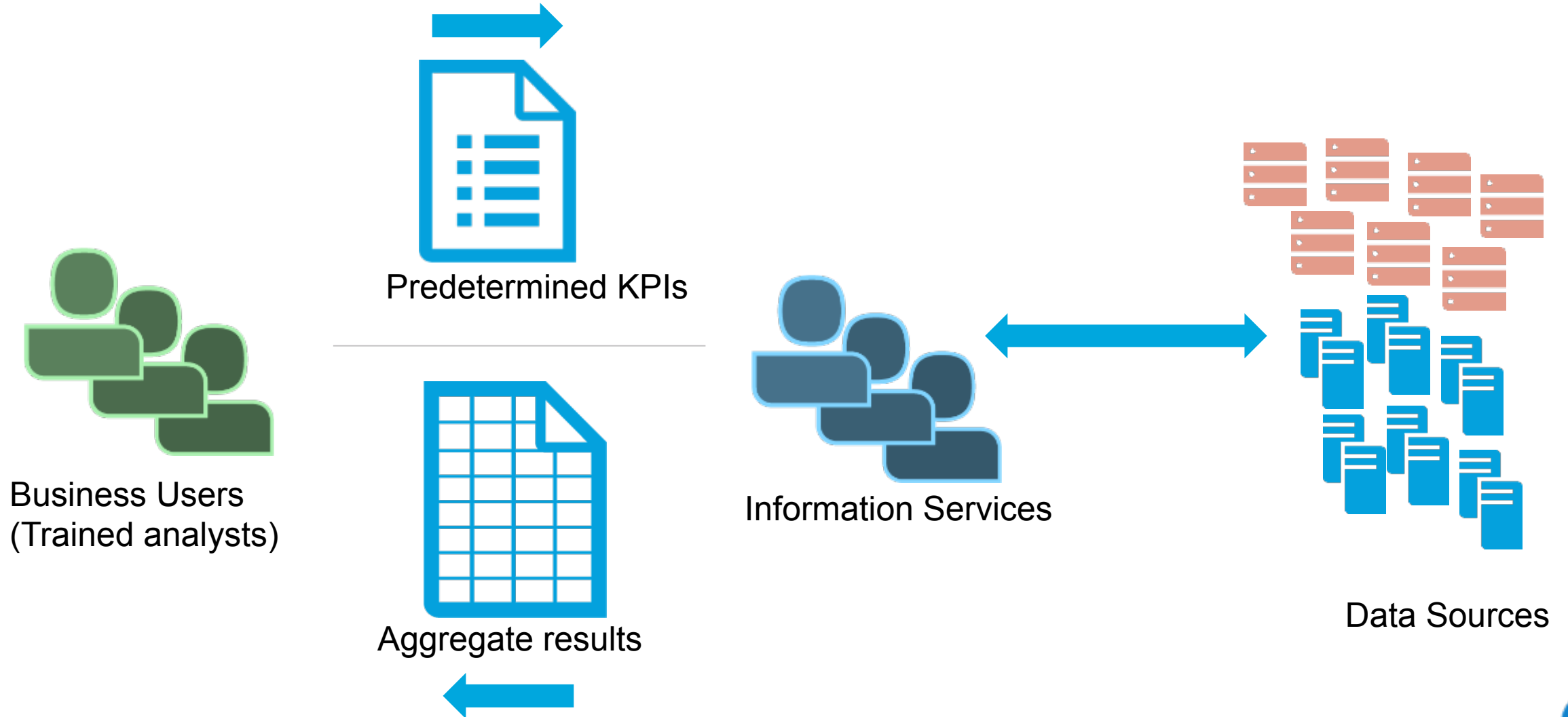
Challenges in Healthcare analytics

- A large portion of clinical records are unstructured (free-text)
- Structured data can be *immense* (eg, genomics)
- Data is in multiple systems and not normalized
- Unstructured clinical data is not leveraged effectively
- Free-text is not standardized nomenclature - users have individual styles and terminology preferences.



Current approach

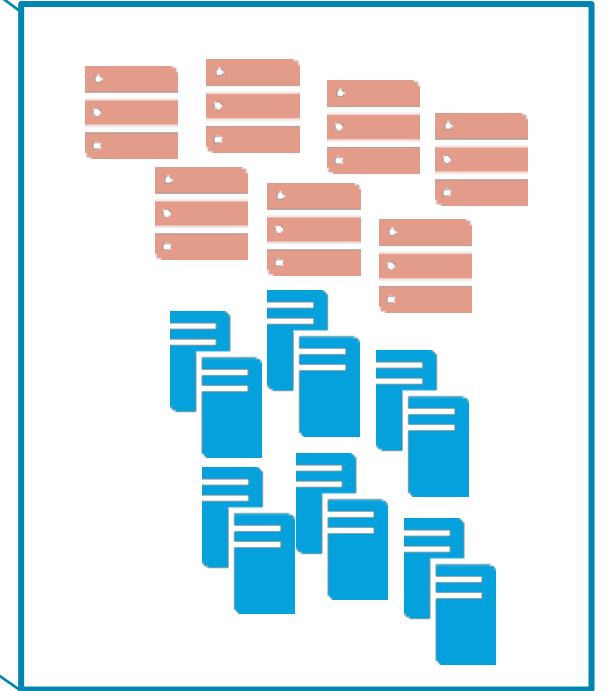
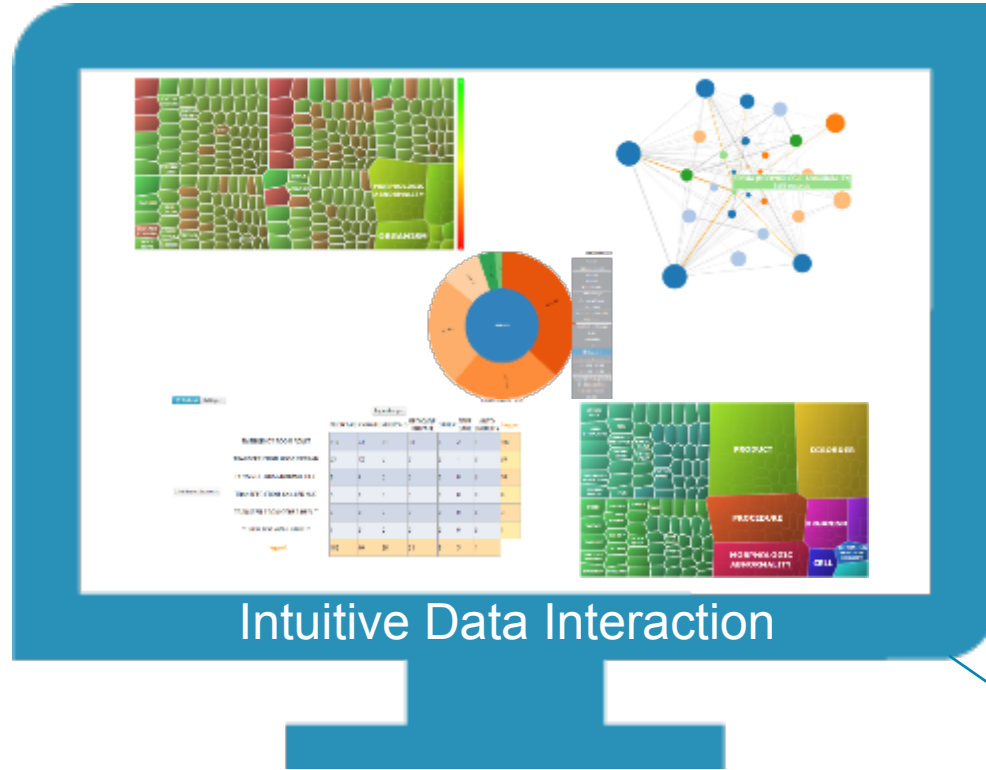
Significant barriers between data and information



Better approach: *Self Service Analytics on all data* Accelerates access to comprehensive insights



Business
Users



Data



Stanford Children's Health



Stanford
Children's Health

Lucile Packard
Children's Hospital
Stanford

- **Background:**

- 312 beds
- Founded in 1991
- Part of the Stanford University system
- Located in Palo Alto, California
- over 650 physicians, 4,750 staff and volunteers
- It specializes in the care of babies, children, adolescents, and expectant mothers

LPCH is rated as the #10 best children's hospital in the United States by U.S. News & World Report

LPCH wins the national award for Excellence in Pediatric Patient Care from the Child Health Corp of America

HP/LPCH text analytics collaboration history:

- **2012: Multi-Patient Semantic Search**
- **2013: Development Partnership, Pilot – US News & World Report Survey**
- **2014: Informatics Transition**
- **2015: Quality improvement – VTE Surveillance**



Stanford Children's Health – USNWR Project

- **Business Owners: Quality and Clinical Effectiveness Team**
- **Clinical data from 2011 – 2013**
 - ~115k patients, ~390k encounters, ~3 million documents
- **Structured data elements**
 - Patient ID, age
 - Encounter ID, location
 - Diagnosis (ICD) and Procedure (CPT) codes
 - Document metadata (e.g. provider)
- **Unstructured data elements**
 - Clinical documents
 - Radiology reports



Stanford
Children's Health

Lucile Packard
Children's Hospital
Stanford



US News Example: D30 - Kasai Procedure

How many unique patients received Kasai procedures?

- Querying by ICD-9 and CPT (ICD-9-CM codes 51.37, OR CPT code 47701)
- Querying by SNOMED concept

How many were considered a surgical success?

- Labor intensive manual chart review (i.e., improvement total in bilirubin <10 mg/dL, no synthetic dysfunction, no surgical complications, delayed need for liver transplant) two years after initial diagnosis?
- Querying by conceptual search (“failed kasai”, “BAFK”)



Expanding use-cases: Hospital acquired Conditions (HAC) Surveillance

Informatics transition at LPCH

- EMR conversion from Cerner to Epic in May, 2014
- New EPIC records: 750k encounters, 155k patients, ~1M notes
- Weekly batch updates ensures data currency

Example of Traditional VTE surveillance workflow

- Initial cohort based on ICD codings is followed by time intensive manual chart abstraction. Identifies 3-5 possible VTE events/month.

HP healthcare analytics assisted workflow

- Initial cohort based on ICD codings and computerized semantic search is followed by computer assisted chart review. Identifies 15-30 possible VTE events/month.



Stanford
Children's Health
Lucile Packard
Children's Hospital
Stanford



Privacy and security implications of big-data

- **Governance of protected health information**
 - Granular access
 - Audit trails
- **Compliance issues**
 - Potentially sampling every record on every query
 - Aggregate vs detailed presentation of data
- **Labeling intended use appropriately**
 - Research use
 - Clinical use
- **Stanford Children's approach**

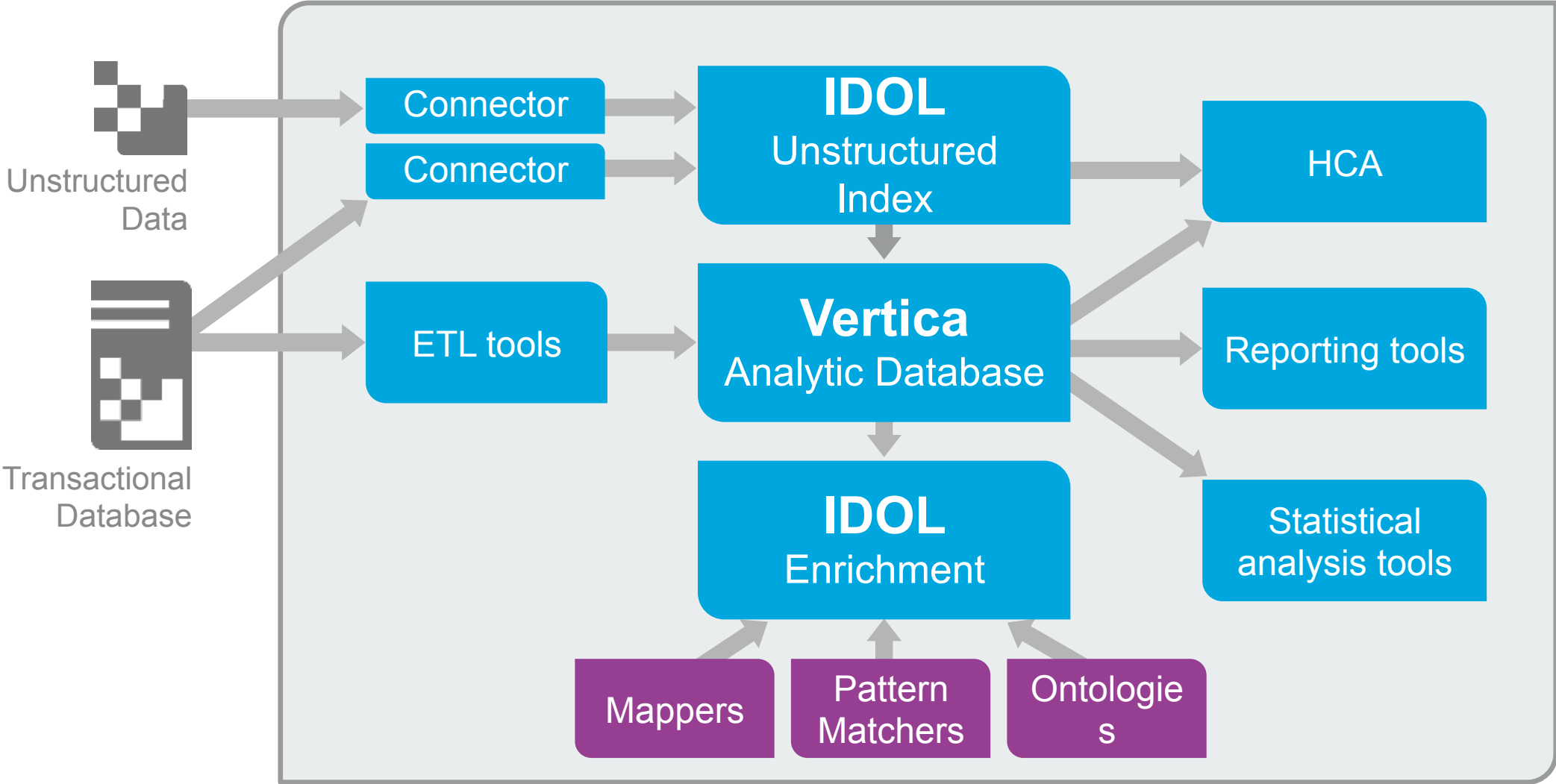


Other examples of self-service analytics use-cases

- **Emergency Room Utilization** – Why does 1% of population use 10% of resources?
- **Discharge level-of-care analysis and planning** – How do we discharge to lowest level of care that maintains good outcomes?
- **Phenotype identification, correlation with genotype variants** – What is the association between gene variant clusters and clinical feature presentation?
- **CT urography assessment for renal/bladder stone positivity, time-in-motion analysis from registration > scan > read** – Which clinicians make CT urography referrals with extremely low-positivity rates?
- **Computer guided Sepsis DRG coding** – How do we improve the accuracy and efficiency of Sepsis coding assignments?



Haven Platform



SNOMED CT

The Global Language of Healthcare



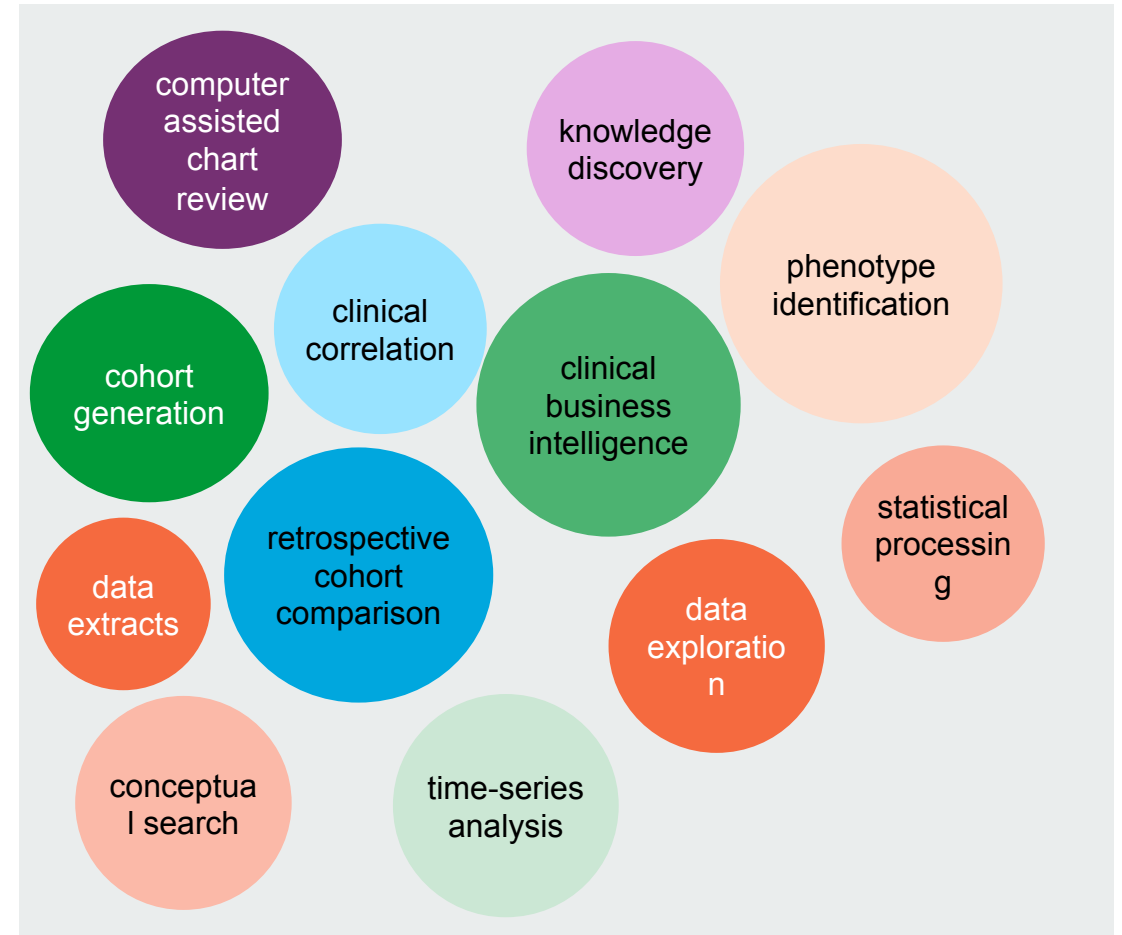
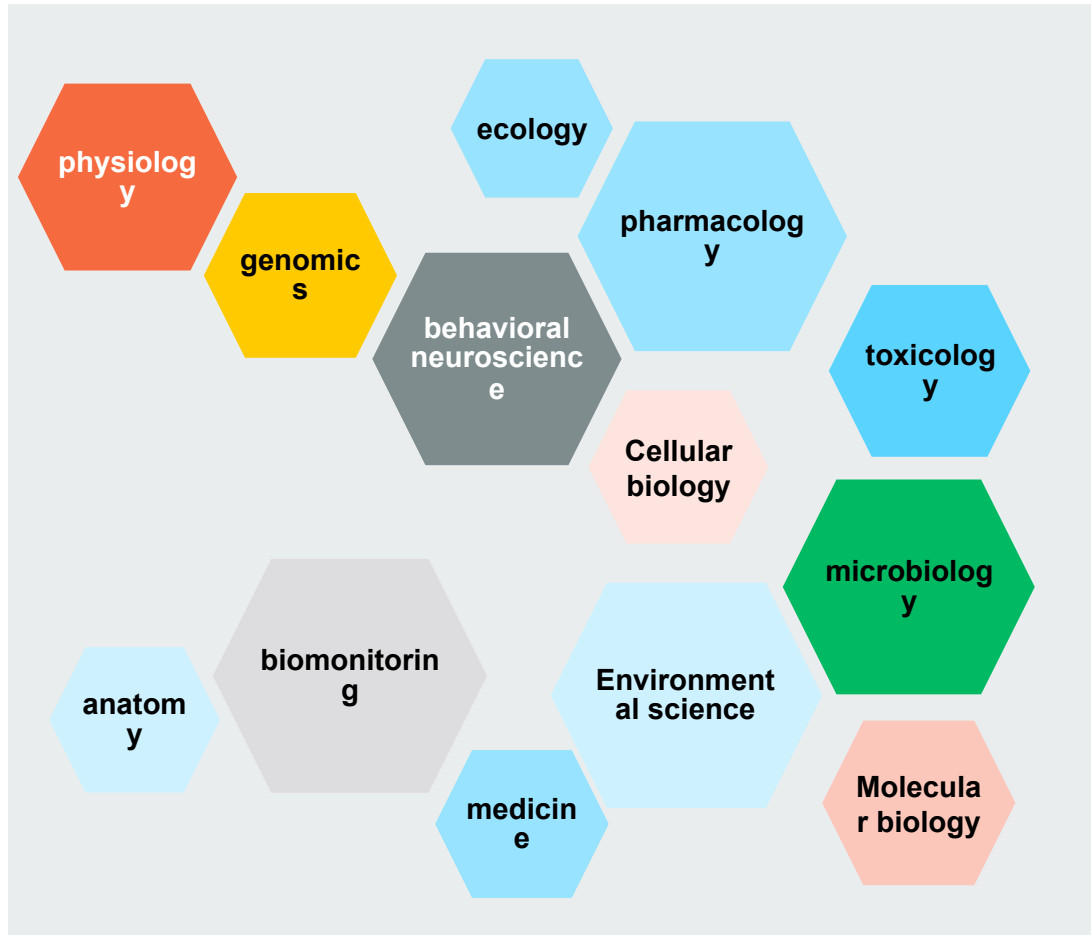
SNOMED CT is the most comprehensive and precise clinical health terminology product in the world, owned and distributed around the world by The International Health Terminology Standards Development Organisation (IHTSDO)

SNOMED CT has been developed collaboratively to ensure it meets the diverse needs and expectations of the worldwide medical profession and is now accepted as a common global language for health terms.

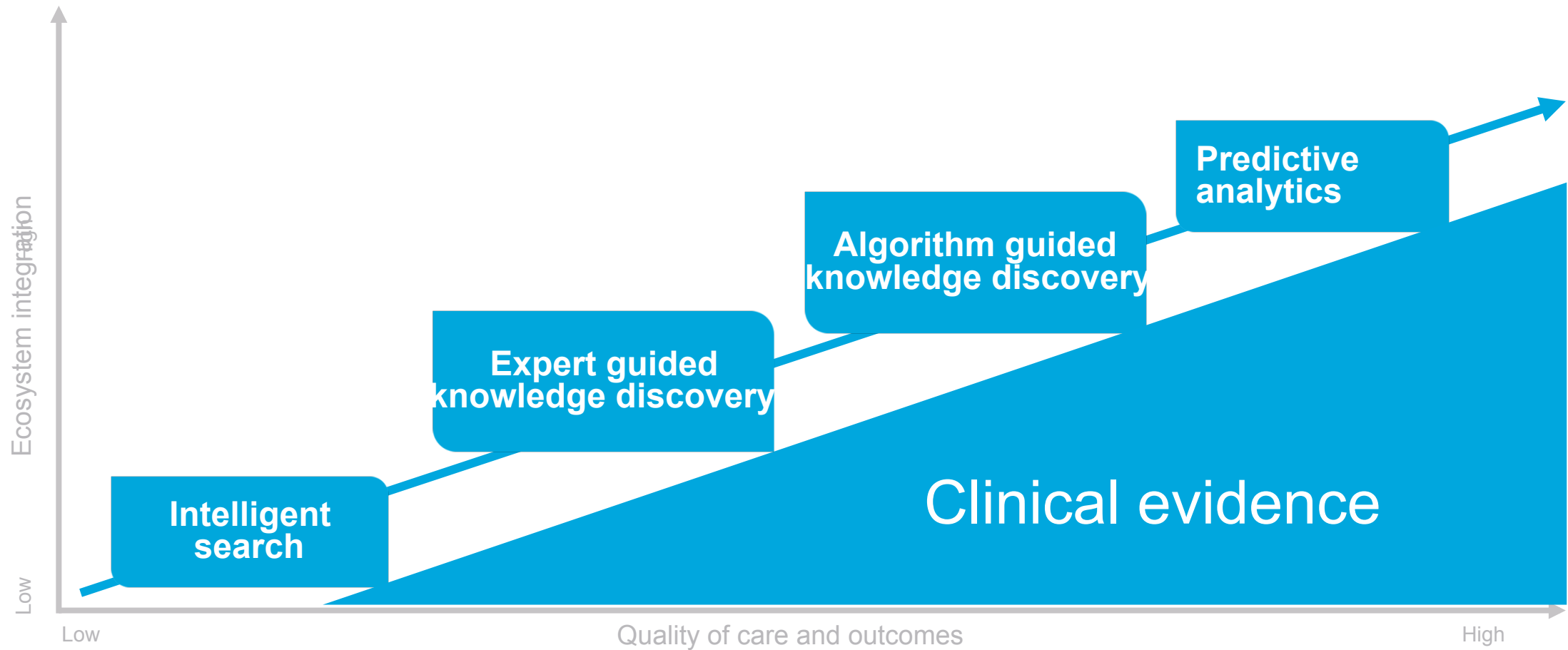
<http://www.ihtsdo.org>



Common analytics functionality across a variety of data types



Technology that *Transforms* Healthcare



Acknowledgements & References

Jon Palma, MD MS

Chris Longhurst, MD
MS

Chelsea Nather

Katie Carpenter

Sam Kalbag

William O

Yogesh Vohra

Nathan Wicke

Josh Glandorf

Dale Gray

- Bates DW, Evans DS, Murff E, et al. Detecting adverse events using information technology. *J Am Med Inform Assoc.* 2003;10:115-128.
- Jha AK, Kuperman GJ, Teich JM, et al. Identifying adverse drug events: development of a computer-based monitor and comparison with chart review and stimulated voluntary report. *JAMA.* 1998;5:305-314.
- Melton GB, Hripcsak G. Automated detection of adverse events using natural language processing of discharge summaries. *J Am Med Inform Assoc.* 2005;12:448-457.
- Rochefort CM, Verma AD, Equale T, et al. A novel method of adverse event detection can accurately identify venous thromboembolisms (VTEs) from narrative electronic health record data. *J Am Med Inform Assoc.* 2015;22:155-165.
- Tinoco A, Evans RS, Staes CJ, et al. Comparison of computerized surveillance and manual chart review for adverse events. *J Am Med Inform Assoc.* 2011;18:491-497.





Thank you

lisa.a.gardner@hp.com