Genevieve Melton-Meaux

- Background
  - Electrical Engineering/Computer Science
  - Medical school (Johns Hopkins)
  - Postdoctoral NLM Biomedical Informatics Fellow(Columbia)
  - Residency (Johns Hopkins), Fellowship (Cleveland Clinic)
- Assistant Professor at Minnesota (joint appointment)
- Institute for Health Informatics
  - Improved health care data use for care & quality functions
  - Natural language processing (text-mining)
  - Biomedical terminologies/ontologies
  - Knowledge representation
- Department of Surgery (Colorectal Surgeon)

Medical Informatics for Detection of Adverse Events

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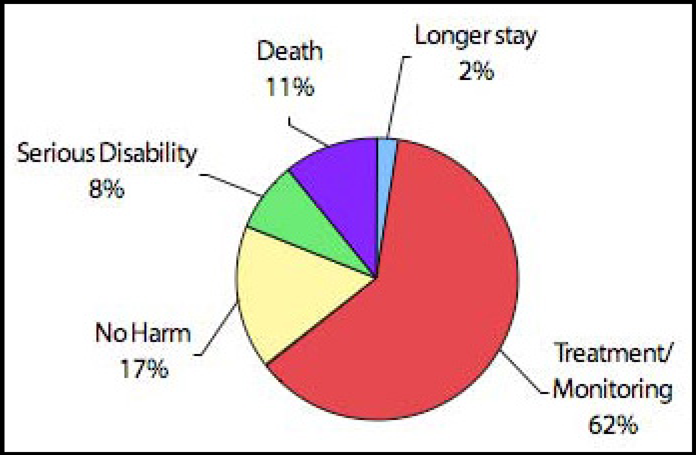
Safety and quality care in medicine

- Adverse event (AE) – defined as injury due to medical management
  - Common and often avoidable
  - Results in increased costs, morbidity, and mortality
- First step in improvement is event detection



Kohn, et al. "To Err is Human: Building a Safer Health System. Institute of Medicine." 1999.

AE detection in medicine

- Potential benefit: Improve patient outcomes with detection
  - If an error or adverse event is not detected, it cannot be managed - "an opportunity missed"[1]
  - Detection can help improve cognitive processes surrounding possible future events
  - Place resources into more *targeted* prevention efforts

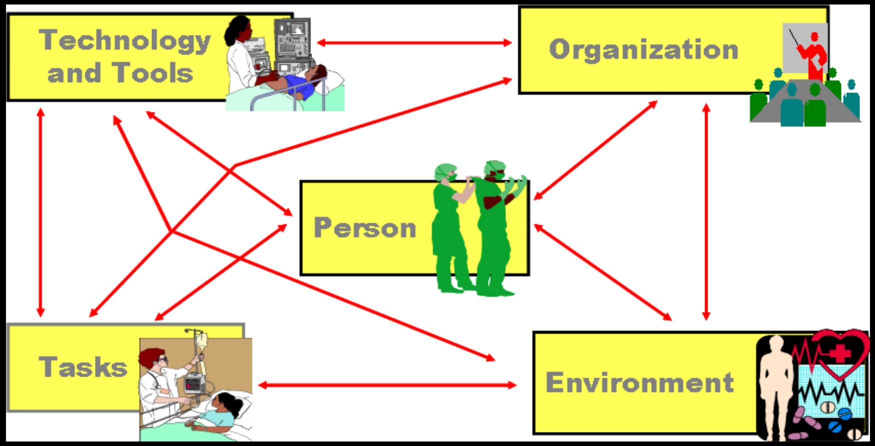
[1]Zapt, et al. "Introduction to error handling." 1994.

Why are AEs classically under-appreciated and under-reported?

- The practice of healthcare is complex
- Spontaneous reporting - unsuccessful at most health care institutions
- Difficulty distinguishing poor outcome with poor care (avoiding "blame")
- Changing with new "culture of safety"
- Manual chart review is resource intensive

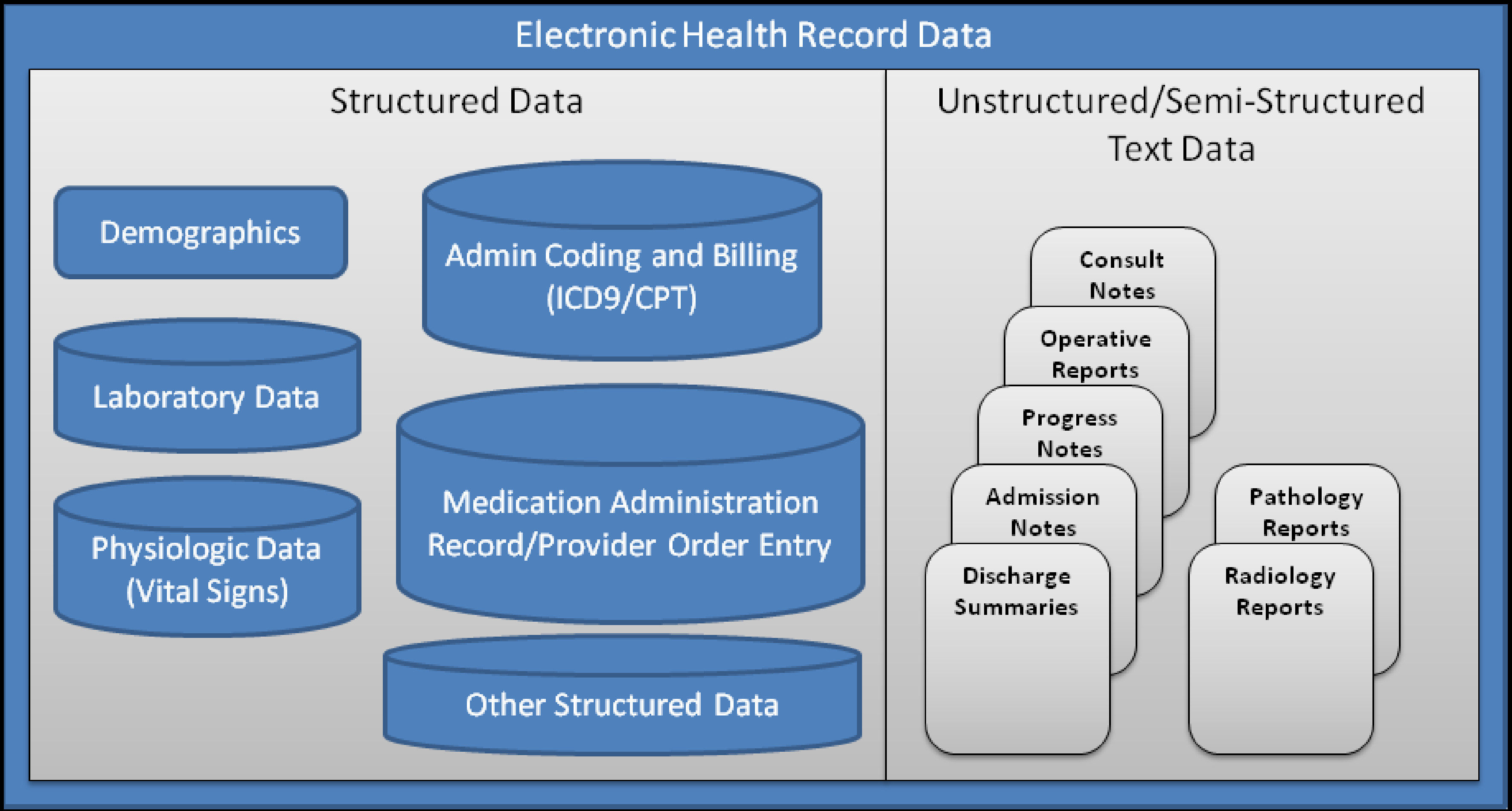
Automated AE detection

- Computerized detection - potential solution
  - Focus is to identify signals suggesting possible presence of AE as a screening method
  - Still typically requires manual verification, allowing for resources to be focused more judiciously[1]



[1]Jha AK, Kuperman GJ, Teich JM, Leape L, et al. "Identifying adverse drug events: development of a computer-based monitor and comparison with chart review and stimulated voluntary report." JAMIA 1998.

Electronic Health Record Data



Steps in Developing an Automated Screening Tool

Patient data in electronic form

Apply queries, rules, algorithms, or other informatics tools

Determine predictive value of tool

Important Issues

I. Type of Data

II. Type of Tool

III. Type of AE

Bates DW, Evans R, Murff H, et al. “Detecting adverse errors using information technology.” JAMIA 2003.

AE detection techniques

- Heuristic rules
  - Perform well in certain settings
  - Rely heavily on intuitive "triggers" for detection

[1]Taft LM, Evans RS, Shyu CR, et al. "Countering imbalanced datasets to improve adverse drug event predictive models in labor and delivery. J Biomed Inform 2009.

AE detection techniques

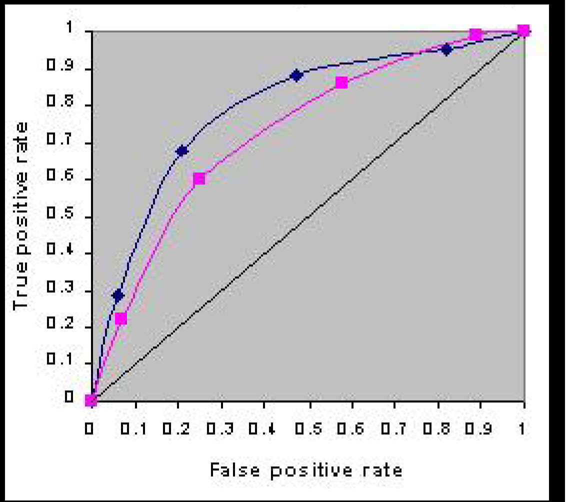
- Heuristic rules
  - Perform well in certain settings
  - Rely heavily on intuitive "triggers" for detection
- Datamining/machine learning techniques
  - Work best with frequent, well-defined events
  - Need adequate training sets to optimize
  - Classic machine learning techniques often fail for datasets with low incidence (sparse)

    Techniques for providing balance to datasets[1]

[1]Taft LM, Evans RS, Shyu CR, et al. "Countering imbalanced datasets to improve adverse drug event predictive models in labor and delivery. J Biomed Inform 2009.

AE detection: predictive trade-offs

- Must consider relative importance and cost of false negatives and false positives
  - Varies by system – weigh by clinical indication
  - Detecting more AE - cost of extra screening (↑FP)
  - Versus cost of missing AE cases (↑FN)
- Minimizing false negatives best in a majority of cases (maximizes detection rate)



Defining AE

- Centralized AE nomenclatures with standardized definitions not settled upon
- National initiatives needed to expand and bring consensus
- Some AE classification systems have been proposed according to setting or discipline
  - JCAHO Patient Safety Event Taxonomy
  - Clavien-Dindo Classification of Surgical Complications

ADEs

- Adverse drug events (ADEs): one of the most common and costly AEs (~100,000 deaths/yr)
- ADEs occur at different points in med lifecycle

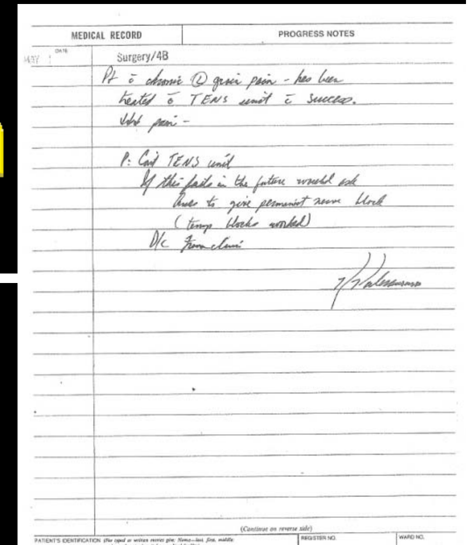
  Ordering (55%) Administration (35%)

  Transcription (5%) Dispensing (5%)
- Computerized provider order entry (CPOE)
  - Allow for ADEs to be detected and prevented
  - Includes alerts and reminders about drug prescribing

ADEs

- Recent review of CPOE for reduction of ADEs (Ammenwerth E et al. JAMIA 2008)
  - 6/9 studies Potential ADEs: RR 35-95%
  - 4/7 studies Actual ADEs: RR 30-80%
  - Still need more systematic analyses of ADE detection strategy costs and benefits
  - Has potential for active real time surveillance

Text data for AE detection



- Clinical documents are promising data sources for AE detection
  - Contain concepts like clinical reasoning, signs and symptoms, summarization, and physical findings
  - Significant challenges to its automated use in the medical domain
  - Goal is to unlock information from text for high through-put uses

Text data challenges

- Documents are variably formatted
  - Section headers
  - Tabular or other spatial formatting
  - Transcription errors (i.e. spelling or grammar)
- Medical term issues
  - Synonymy, Related/similar terms, Abbreviations (often redundant), Context-specific meanings
- Challenge for dealing with uncertainty, negation, and timing

Medical NLP for AE detection

- MedLEE, medical natural language processing (NLP) application[1]
  - Developed to process radiographic reports
  - Expanded for other medical texts
- Uses a vocabulary and grammar to extract data from text
  - Handles negation(denial), uncertainty, timing, synonyms, and abbreviations
  - Structured output for automated processing

[1]Friedman C, et al. “A general natural-language text processor for clinical radiology.” JAMIA, 1994.

MedLEE output example

Example sentence:
“The patient may have a history of MI”

NLP application coded output:

- problem: myocardial infarction
- certainty: moderate
- status: past history

Automated AE Detection in Discharge Summaries using NLP

- Data source: Discharge summaries from CPMC in the clinical data repository
  - 1990-1995 (training set)
  - 1996 and 2000 (test set)
- NLP Tool:
  - MedLEE (Medical Language Extraction and Encoding System)
  - Form semantically complex queries to detect AE from NLP output

[1]Melton GB and Hripcsak G. "Automated detection of adverse events using natural language processing of discharge summaries." JAMIA, 2005.

Automated AE Detection in Discharge Summaries using NLP

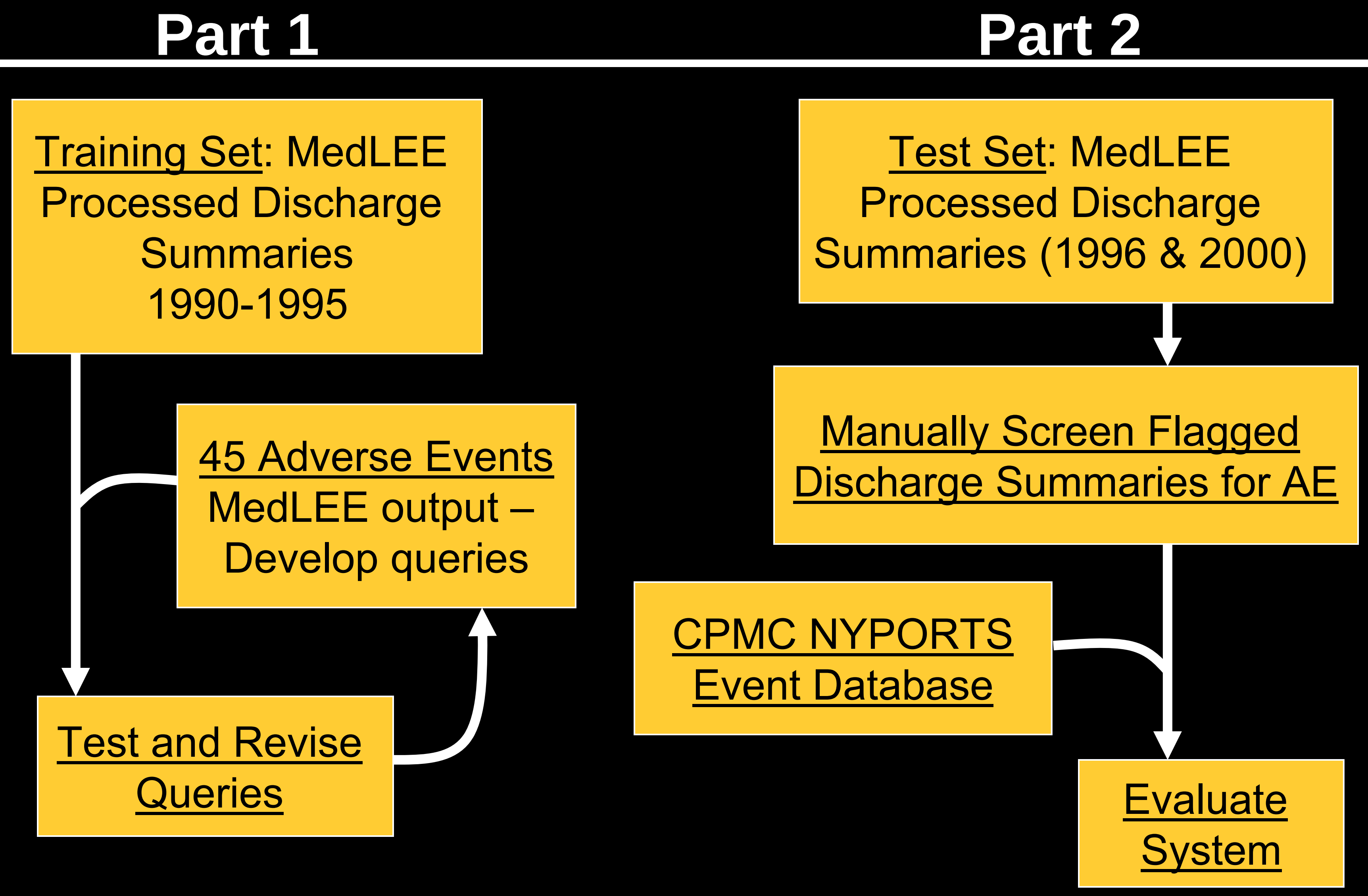
- Adverse events structure: New York State Patient Occurrence Reporting and Tracking System (NYPORTS)
- Evaluate performance of tool and compare system to institutional risk-management reporting database

[1]Melton GB and Hripcsak G. "Automated detection of adverse events using natural language processing of discharge summaries." JAMIA, 2005.

NYPORTS Structure

- Mandatory AE reporting framework for health care institutions in New York (instituted 1996)
- 50 events: 45 events related to patients
- Several AE also require a “root cause analysis” with their reporting
- Many AE semantically complex with several prerequisite conditions for qualification

Study Design Schematic



NYPORTS –Adverse Events: Semantic Complexity

- **Laparoscopic:** "All unplanned conversions to an open procedure because of an injury and/or bleeding during the laparoscopic procedure."
  - Excludes:
    - Diagnostic laparoscopy with a planned conversion
    - Conversion based upon a diagnosis made during the laparoscopic procedure
    - Conversions due to difficult anatomy
- Intravascular Catheter Related Pneumothorax: Regardless of size or treatment
  - Excludes: "Non-intravascular catheter related pneumothoraces such as those resulting from lung biopsy, thoracentesis, permanent pacemaker, etc."

Generating Complex Queries - Example

Rule: In Hospital Course, History of Present Illness, or Discharge Diagnosis Section:

laparoscopic, injury, no trauma, and "convert/conversion"

OR

laparoscopic, injury, open procedure, all three in same paragraph, and no trauma

1) Laparoscopic: laparoscopic cholecystectomy, laparoscopy OR ** +proceduredescr: laparoscopy
2) Open procedure:** +descriptor:open
3) Trauma: stabbed, stab wound, gunshot wound
4) Injury: injury, bleeding, hemorrhage, laceration, oozing, perforated

(1-4) exclude if: Certainty:no,rule out,very low certainty, ignore, cannot evaluate,negative,low certainty OR Status:resolved,removed,removal, end,healed,inactive,past history,history,rule out,unknown

Overall System Performance

Total discharge summaries	57452
System P	1590
System TP	704
CPMC T	294
Both System TP and CPMC T	78
System Precision (95% CI) pooled events	**0.44 (0.419, 0.466)**
System Precision (95% CI) per event	**0.44 (0.234, 0.653)**
System Recall (95% CI) pooled events	**0.27 (0.220, 0.310)**
System Recall (95% CI) per event	**0.27 (0.042,0.495)**
CPMC Recall (95% CI) pooled events	**0.11 (0.057, 0.165)**
CPMC Recall (95% CI) per event	**0.11 (0.054, 0.280)**

AE detection with NLP from discharge summaries

- Applied detection of AE with NLP
  - System precision of 44%
  - System over tripled NYPORTS AE detected
  - System performance comparable to other detection tools but with more complex AE
- Limitations
  - Manually reported events and automated NLP detection find different AE
  - Other documents types
  - Patient stays without discharge summary generation

[1]Melton GB and Hripcsak G. "Automated detection of adverse events using natural language processing of discharge summaries." JAMIA, 2005.

Conclusion

- AE detection important for prevention strategies to improve medical care
- Challenges in system development
  - Tailor to available data and type of AEs
  - Development of AE standards
  - Balancing FP/FN
- Extensible tools (multi-site/ multi-system)

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[redacted]

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Coded Data and Screening Tools

- Administrative data coding
- Pharmacy and clinical laboratory data
- Workflow-based computer systems
  - Computerized provider order entry (CPOE)
  - Ambulatory care systems
- Standardized formats for ancillary reports

Precision and Recall (Information Retrieval)

- **Precision** = *number of relevant documents* retrieved by search *divided by total number of documents retrieved* by search
  - Measure of exactness/fidelity
- **Recall** = *number of relevant documents* retrieved by search *divided by total number of existing relevant documents* (which should have been retrieved).
  - Measure of completeness