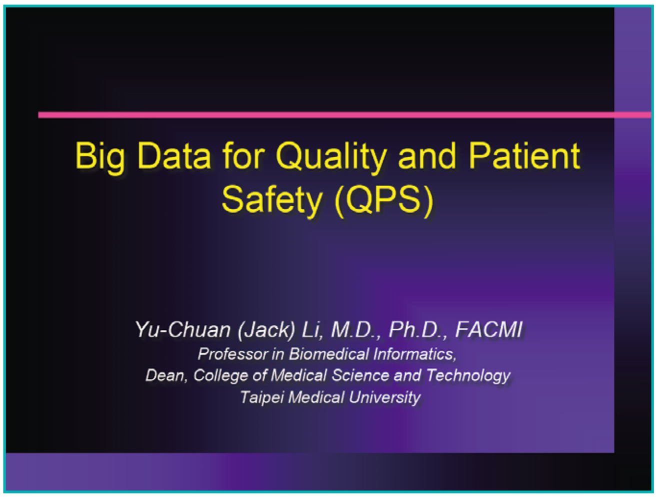
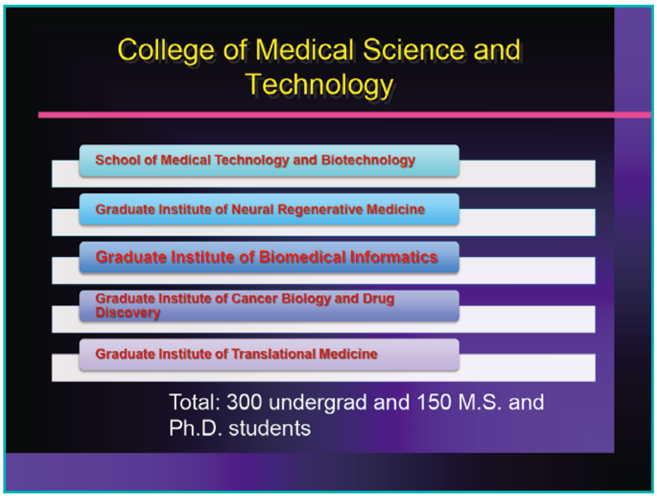
[Taiwan]

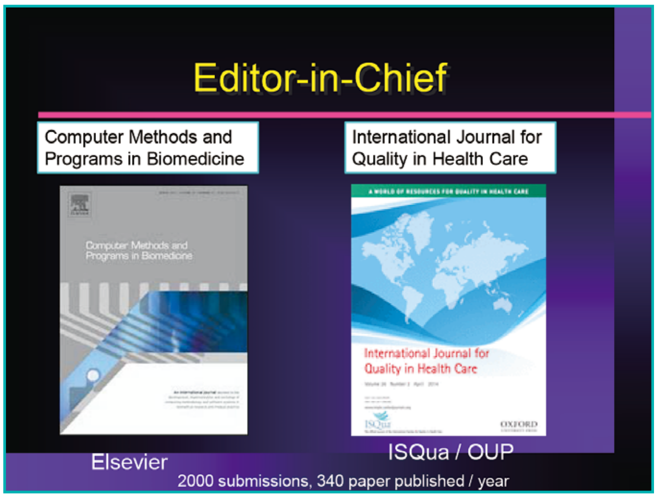
The Health Database in an Information Society[*1]

Yu-Chuan (Jack) LI[1]

Besides paperless-ness and efficiency, the most valuable application of accumulated, aggregated Electronic Health Record data may well be their use to improve quality and patient safety. This talk describes a Data Interaction Model (DIM) and a Probabilistic Association Model (PAM) that would allow healthcare professionals a new perspective to look at their own Big Data, while also provides an architecture to fully take advantage of the data in hands to continuously improve healthcare quality and patient safety.

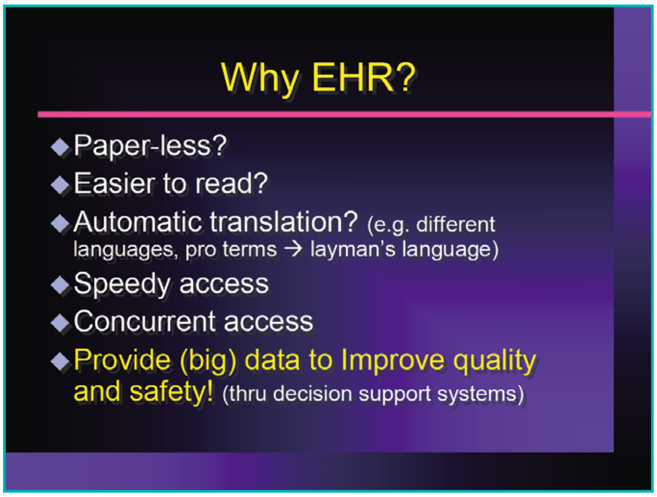


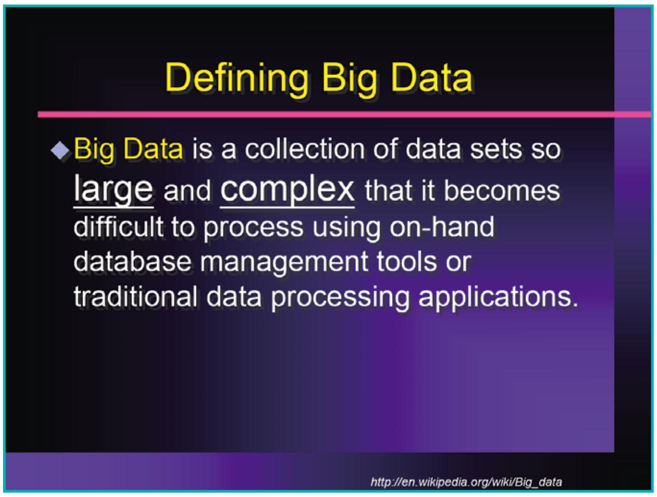


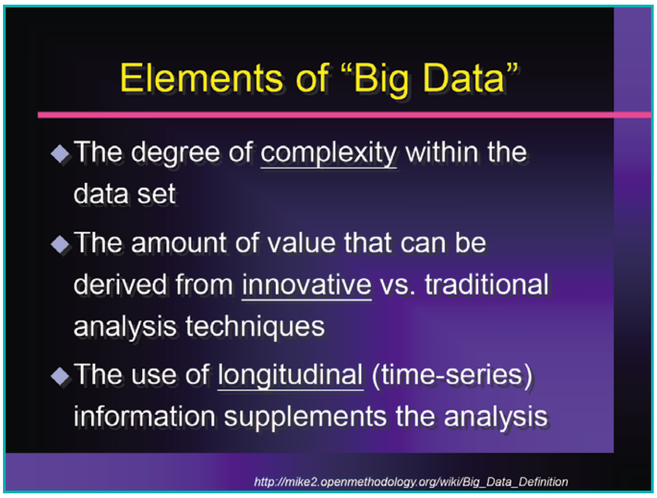


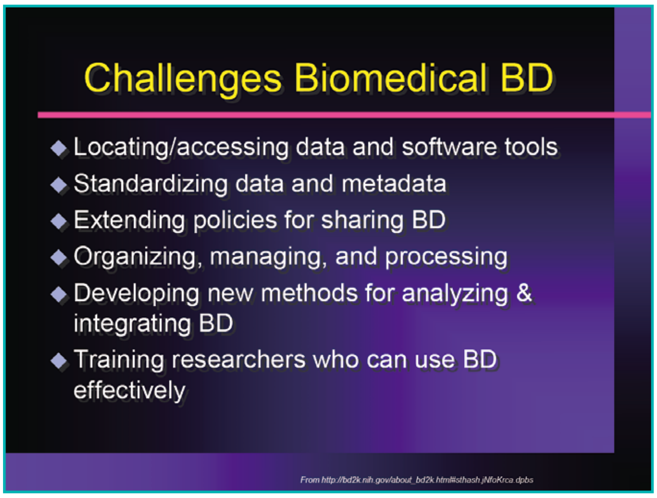
*1 This article is base on a presentation made at the Symposium "Health Database in an Information Society" held at the 29th CMAAO General Assembly and 50th Council Meeting, Manila, the Philippines, on September 24-26, 2014.

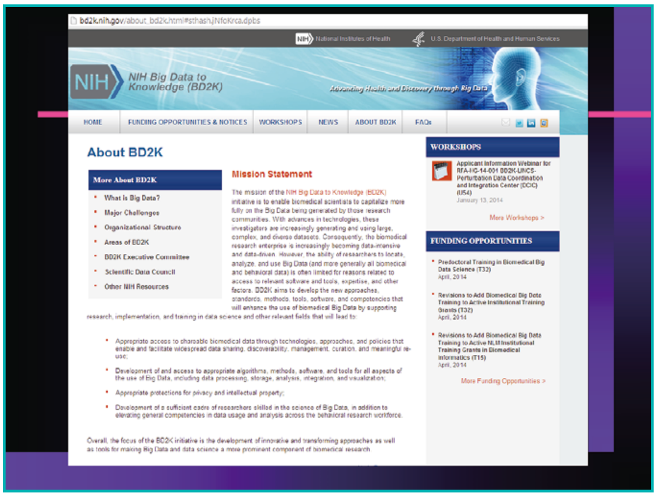
1 Professor in Biomedical Informatics, Dean, College of Medical Science and Technology Taipei Medical University, Taipei, Taiwan. (intl@tma.tw).

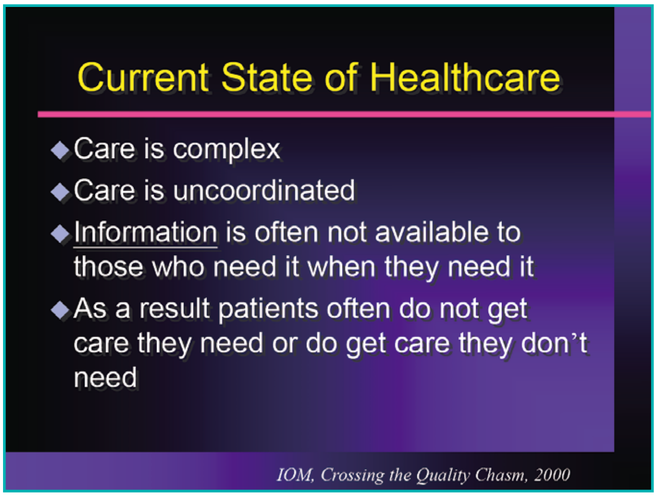

Why EHR?
◆Paper-less?
◆Easier to read?
◆Automatic translation? (e.g. different languages, pro terms → layman's language)
◆Speedy access
◆Concurrent access
◆Provide (big) data to Improve quality and safety! (thru decision support systems)

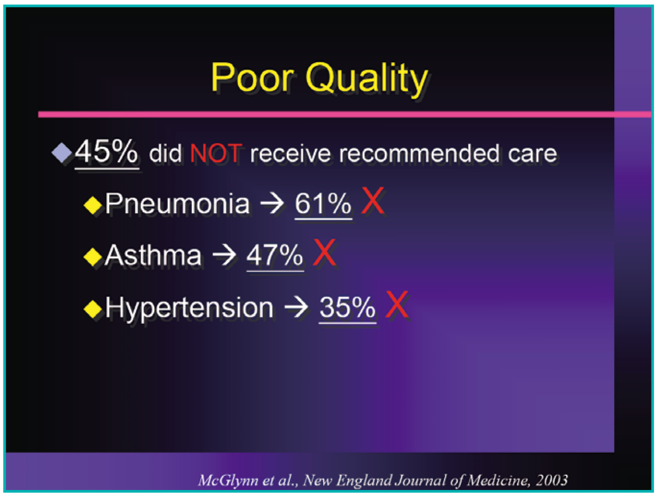

Defining Big Data
◆Big Data is a collection of data sets so large and complex that it becomes difficult to process using on-hand database management tools or traditional data processing applications.
http://en.wikipedia.org/wiki/Big_data

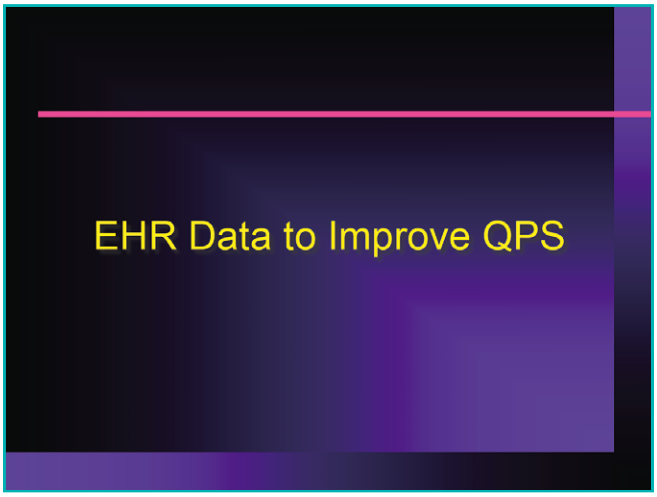

Elements of "Big Data"
◆The degree of complexity within the data set
◆The amount of value that can be derived from innovative vs. traditional analysis techniques
◆The use of longitudinal (time-series) information supplements the analysis
http://mike2.openmethodology.org/wiki/Big_Data_Definition

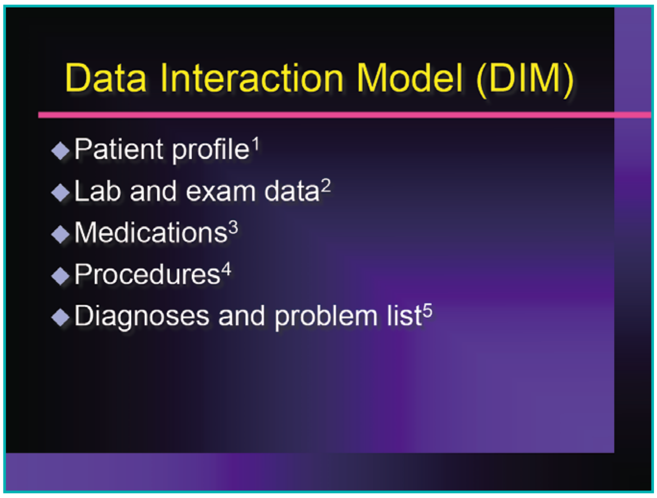

Challenges Biomedical BD
◆Locating/accessing data and software tools
◆Standardizing data and metadata
◆Extending policies for sharing BD
◆Organizing, managing, and processing
◆Developing new methods for analyzing & integrating BD
◆Training researchers who can use BD effectively
From http://bd2k.nih.gov/about_bd2k.html#sthash.jNfoKrca.dpbs

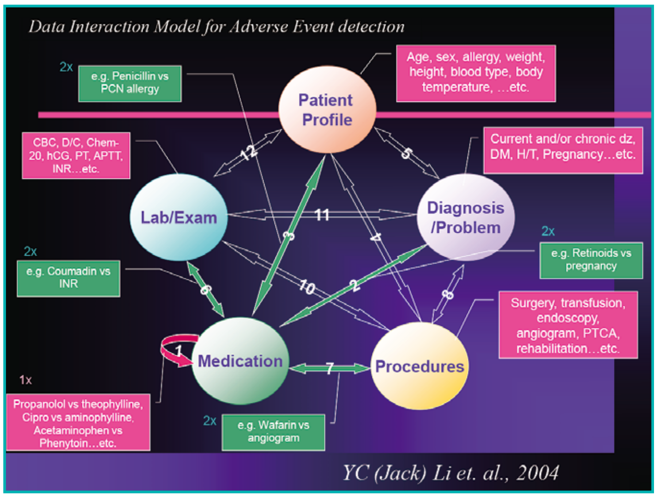

NIH Big Data to Knowledge (BD2K)
HOME
FUNDING OPPORTUNITIES & NOTICES
WORKSHOPS
NEWS
ABOUT BD2K
FAQs
About BD2K
More About BD2K
Mission Statement
WORKSHOPS
FUNDING OPPORTUNITIES

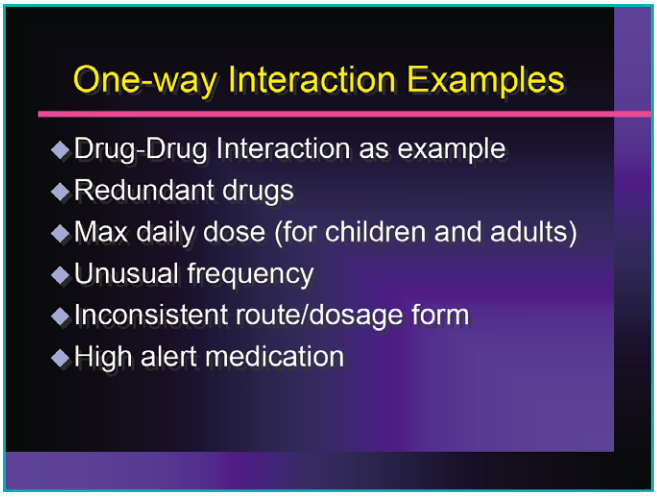

Current State of Healthcare
◆Care is complex
◆Care is uncoordinated
◆Information is often not available to those who need it when they need it
◆As a result patients often do not get care they need or do get care they don't need
IOM, Crossing the Quality Chasm, 2000

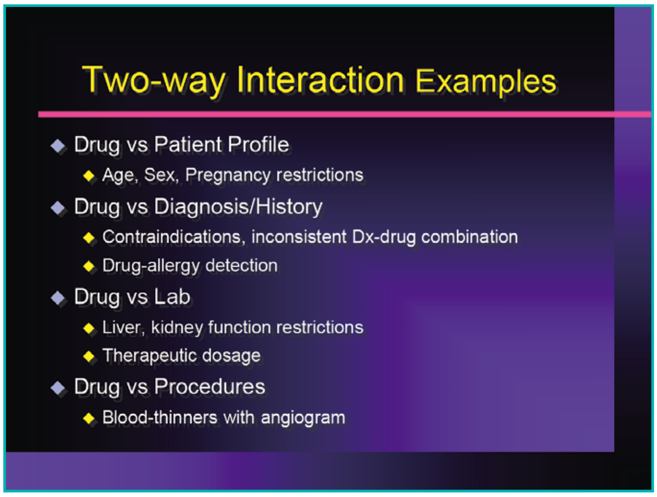

Poor Quality
◆45% did NOT receive recommended care
◆Pneumonia → 61% X
◆Asthma → 47% X
◆Hypertension → 35% X
McGlynn et al., New England Journal of Medicine, 2003

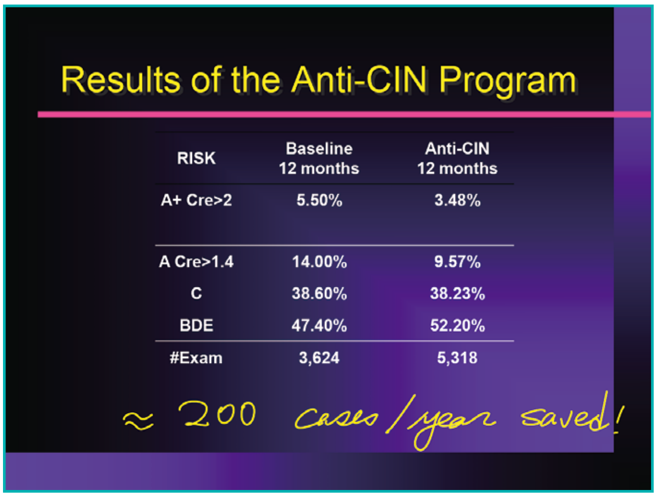

EHR Data to Improve QPS

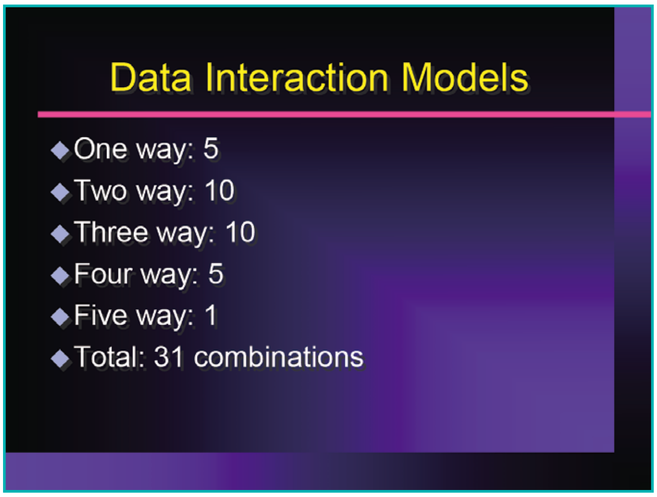

Data Interaction Model (DIM)
◆Patient profile[1]
◆Lab and exam data[2]
◆Medications[3]
◆Procedures[4]
◆Diagnoses and problem list[5]

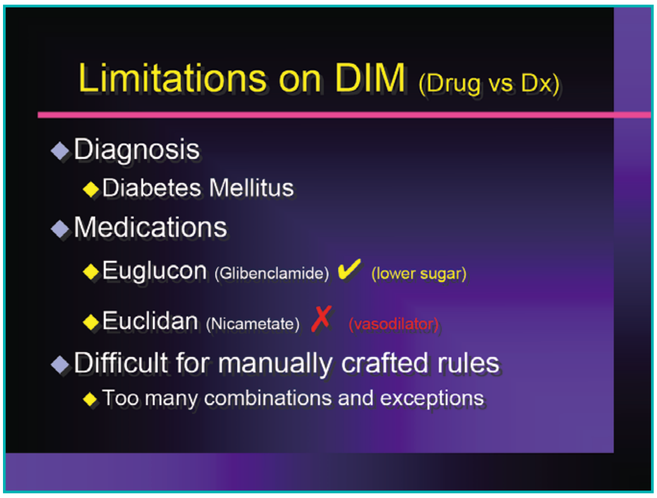

Data Interaction Model for Adverse Event detection
2x
e.g. Penicillin vs PCN allergy
Age, sex, allergy, weight, height, blood type, body temperature, …etc.
Patient Profile
CBC, D/C, Chem-20, hCG, PT, APTT, INR…etc.
Current and/or chronic dz, DM, H/T, Pregnancy…etc.
Lab/Exam
Diagnosis /Problem
2x
e.g. Coumadin vs INR
2x
e.g. Retinoids vs pregnancy
Surgery, transfusion, endoscopy, angiogram, PTCA, rehabilitation…etc.
Medication
Procedures
1x
Propanolol vs theophylline, Cipro vs aminophylline, Acetaminophen vs Phenytoin…etc.
2x
e.g. Wafarin vs angiogram
1
2
3
4
5
6
7
8
10
11
12
YC (Jack) Li et. al., 2004

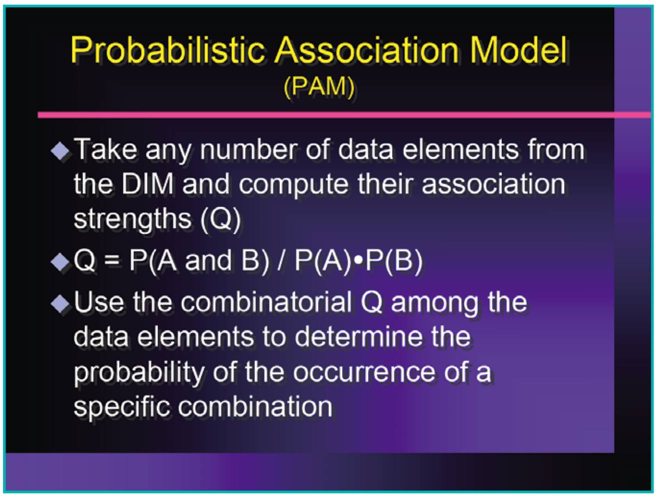

One-way Interaction Examples
◆Drug-Drug Interaction as example
◆Redundant drugs
◆Max daily dose (for children and adults)
◆Unusual frequency
◆Inconsistent route/dosage form
◆High alert medication

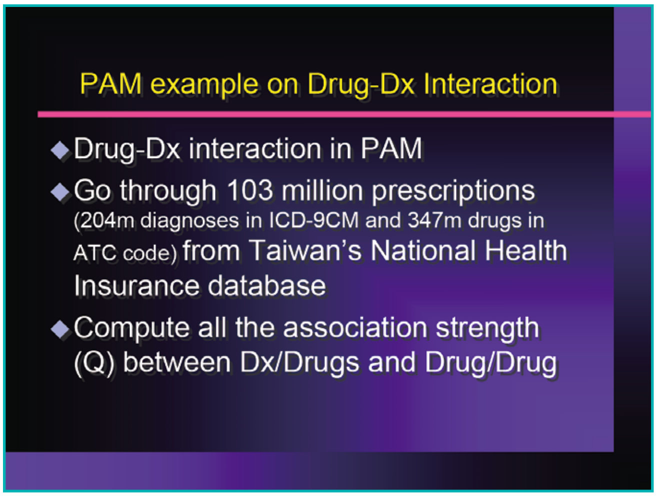

Two-way Interaction Examples
◆ Drug vs Patient Profile
◆ Age, Sex, Pregnancy restrictions
◆ Drug vs Diagnosis/History
◆ Contraindications, inconsistent Dx-drug combination
◆ Drug-allergy detection
◆ Drug vs Lab
◆ Liver, kidney function restrictions
◆ Therapeutic dosage
◆ Drug vs Procedures
◆ Blood-thinners with angiogram

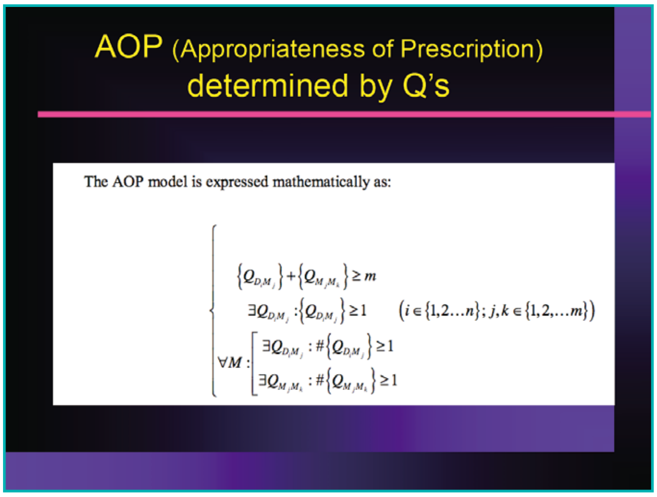

Results of the Anti-CIN Program
RISK | Baseline 12 months | Anti-CIN 12 months
A+ Cre>2 | 5.50% | 3.48%
A Cre>1.4 | 14.00% | 9.57%
C | 38.60% | 38.23%
BDE | 47.40% | 52.20%
#Exam | 3,624 | 5,318
≈ 200 cases / year saved!

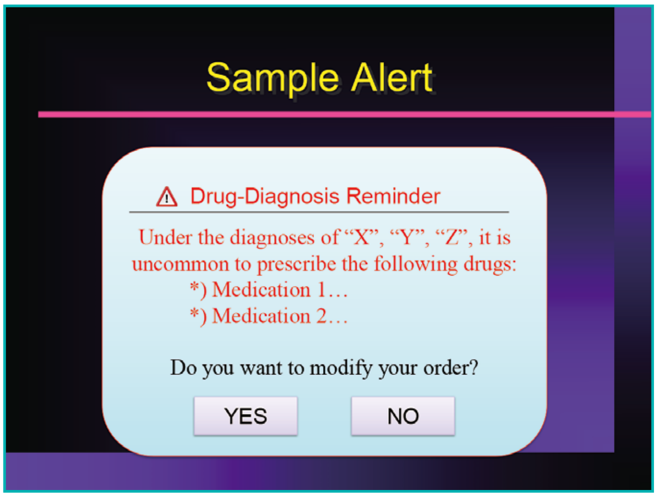

Data Interaction Models
One way: 5
Two way: 10
Three way: 10
Four way: 5
Five way: 1
Total: 31 combinations

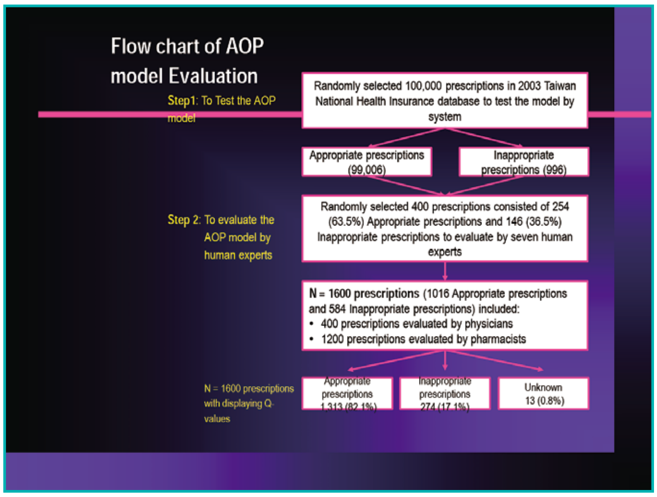

Limitations on DIM (Drug vs Dx)
Diagnosis
Diabetes Mellitus
Medications
Euglucon (Glibenclamide) ✔ (lower sugar)
Euclidan (Nicametate) ✗ (vasodilator)
Difficult for manually crafted rules
Too many combinations and exceptions

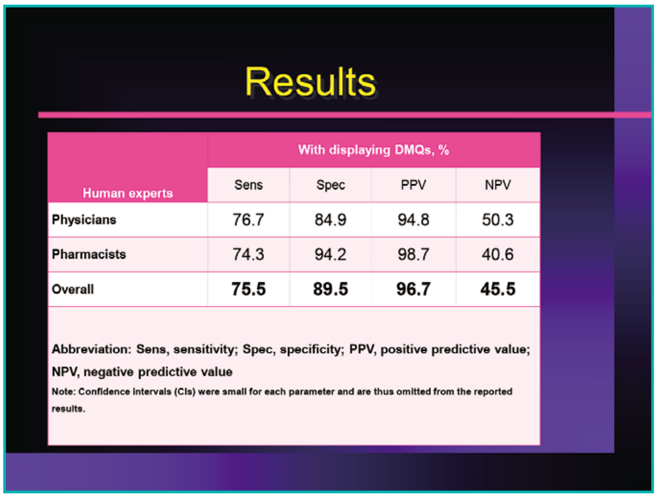

Probabilistic Association Model (PAM)
Take any number of data elements from the DIM and compute their association strengths (Q)
Q = P(A and B) / P(A)•P(B)
Use the combinatorial Q among the data elements to determine the probability of the occurrence of a specific combination


PAM example on Drug-Dx Interaction
Drug-Dx interaction in PAM
Go through 103 million prescriptions (204m diagnoses in ICD-9CM and 347m drugs in ATC code) from Taiwan's National Health Insurance database
Compute all the association strength (Q) between Dx/Drugs and Drug/Drug


AOP (Appropriateness of Prescription) determined by Q's
The AOP model is expressed mathematically as:
$\{Q_{D_iM_j}\}+\{Q_{M_jM_k}\}\geq m$
$\exists Q_{D_iM_j}:\{Q_{D_iM_j}\}\geq 1 \quad (i\in\{1,2\ldots n\};\ j,k\in\{1,2,\ldots m\})$
$\forall M: \exists Q_{D_iM_j}:\#\{Q_{D_iM_j}\}\geq 1$
$\exists Q_{M_jM_k}:\#\{Q_{M_jM_k}\}\geq 1$

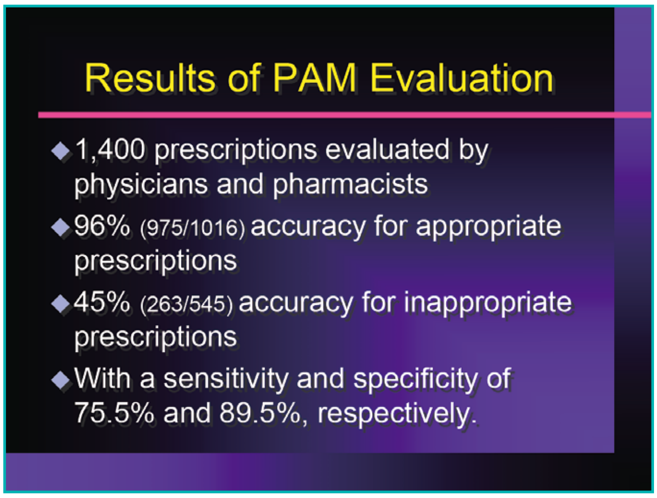


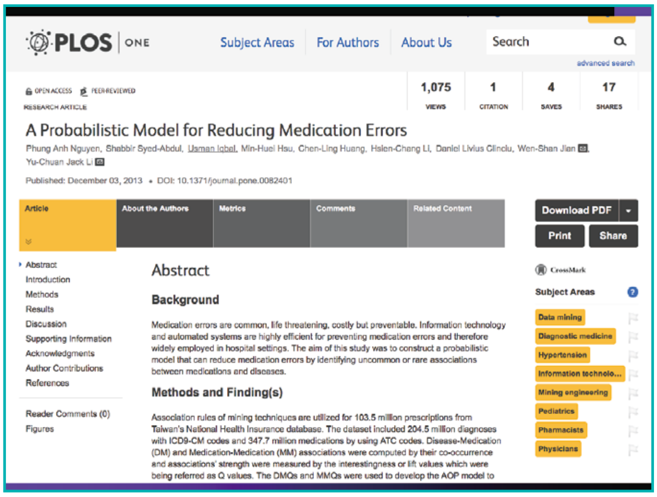




Human experts	With displaying DMQs, %			
	Sens	Spec	PPV	NPV
Physicians	76.7	84.9	94.8	50.3
Pharmacists	74.3	94.2	98.7	40.6
Overall	75.5	89.5	96.7	45.5

Abbreviation: Sens, sensitivity; Spec, specificity; PPV, positive predictive value; NPV, negative predictive value
Note: Confidence intervals (CIs) were small for each parameter and are thus omitted from the reported results.




PLOS ONE
Subject Areas | For Authors | About Us | Search
advanced search
OPEN ACCESS PEER-REVIEWED
RESEARCH ARTICLE
1,075 VIEWS | 1 CITATION | 4 SAVES | 17 SHARES

A Probabilistic Model for Reducing Medication Errors

Phung Anh Nguyen, Shabbir Syed-Abdul, Usman Iqbal, Min-Huei Hsu, Chen-Ling Huang, Hsien-Chang Li, Daniel Livius Clinciu, Wen-Shan Jian, Yu-Chuan Jack Li

Published: December 03, 2013 • DOI: 10.1371/journal.pone.0082401

Article | About the Authors | Metrics | Comments | Related Content
Download PDF | Print | Share

Abstract
Introduction
Methods
Results
Discussion
Supporting Information
Acknowledgments
Author Contributions
References
Reader Comments (0)
Figures

Abstract

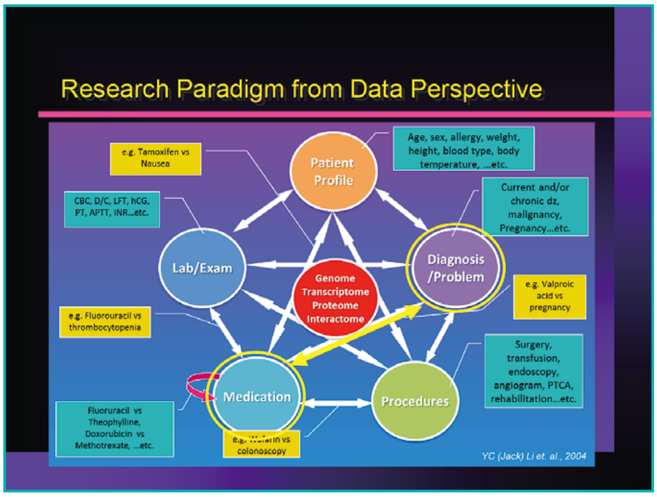
Background

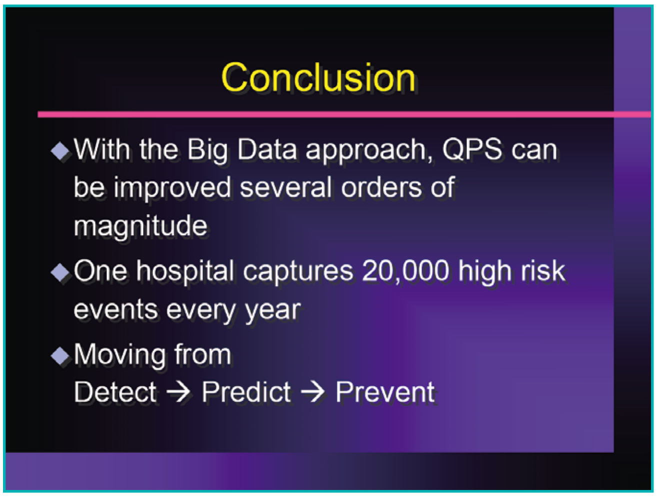
Medication errors are common, life threatening, costly but preventable. Information technology and automated systems are highly efficient for preventing medication errors and therefore widely employed in hospital settings. The aim of this study was to construct a probabilistic model that can reduce medication errors by identifying uncommon or rare associations between medications and diseases.

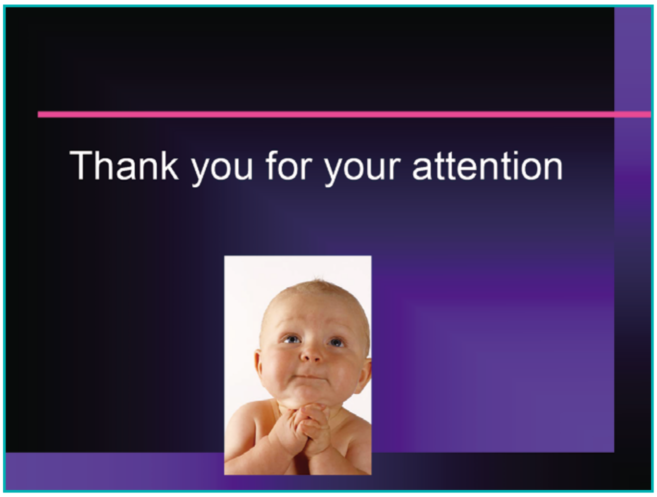
Methods and Finding(s)

Association rules of mining techniques are utilized for 103.5 million prescriptions from Taiwan's National Health Insurance database. The dataset included 204.5 million diagnoses with ICD9-CM codes and 347.7 million medications by using ATC codes. Disease-Medication (DM) and Medication-Medication (MM) associations were computed by their co-occurrence and associations' strength were measured by the interestingness or lift values which were being referred as Q values. The DMQs and MMQs were used to develop the AOP model to

CrossMark
Subject Areas
Data mining
Diagnostic medicine
Hypertension
Information technolo…
Mining engineering
Pediatrics
Pharmacists
Physicians




Conclusion
With the Big Data approach, QPS can be improved several orders of magnitude
One hospital captures 20,000 high risk events every year
Moving from
Detect → Predict → Prevent


Thank you for your attention