Improving Health Decisions; A Statistical Call to Arms

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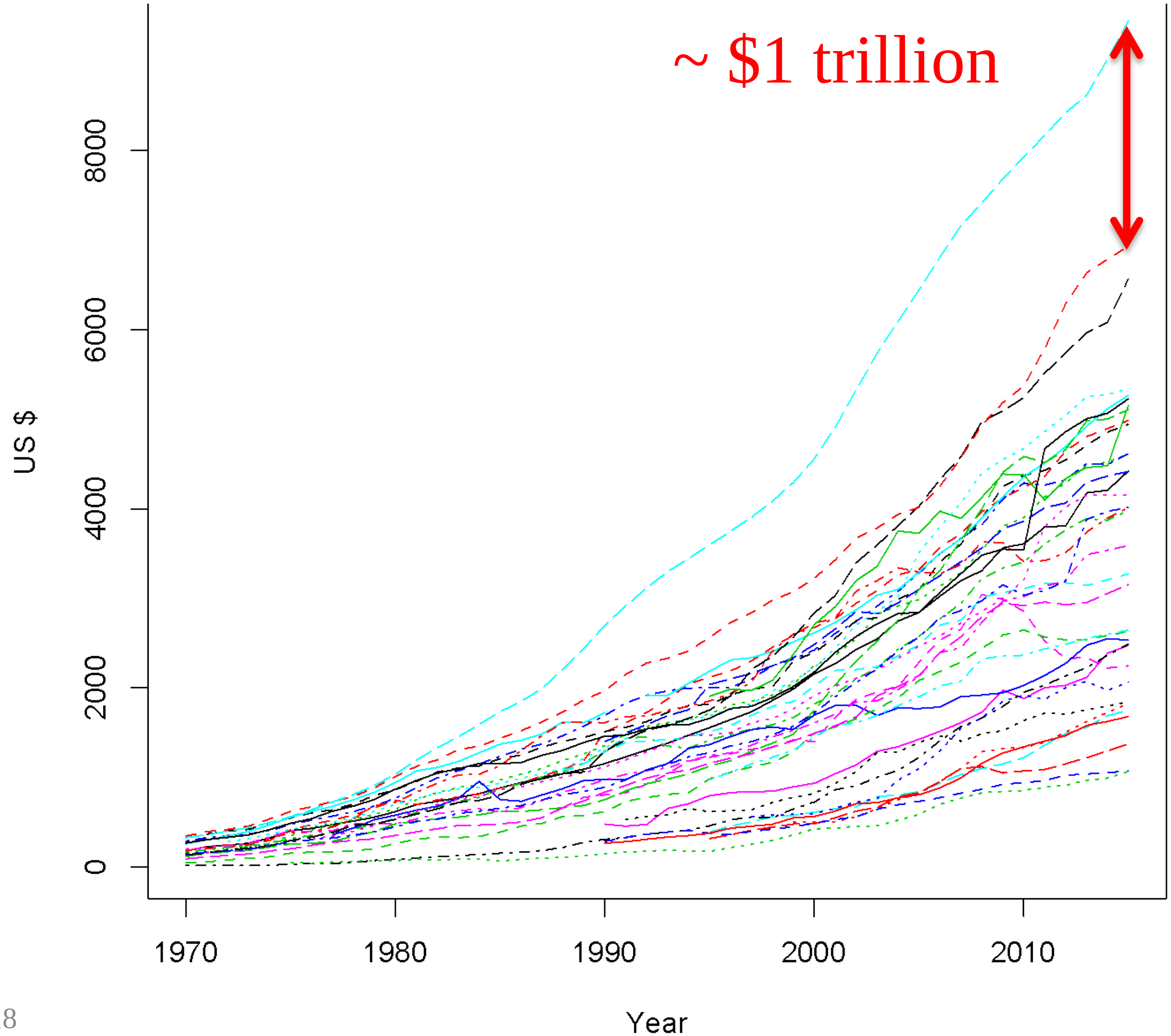
Talk Outline

- The Stew
- Short Review
- What’s New
- Our View

The Stew

Per Capita Annual Medical Expenditures - OECD Countries



Smoking Attributable Costs for 60 Million Who Started Under 21 Years Old, 1954-2000

Disease: LC/COPD (millions case-years)	43.7
Disease: CHD Group (millions case-years)	80.8
Dollars **(billions)**	**1,087**
Deaths **(million years lost)**	**128.0** **(13m persons)**

How Big is 1 Trillion?

- 1,000,000,000,000 – a million millions
- 1 trillion seconds ago was 30,000 BC
- $1 trillion, as a stack of $100 bills, is 630 miles high
- $9,000 per household in the U.S.

Table. Estimates of Annual US Health Care Waste, by Category[a]

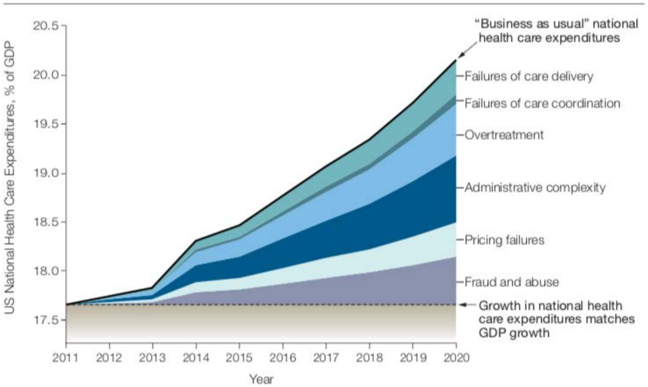
	$ in Billions					
	Annual Cost to Medicare and Medicaid in 2011[b]			Annual Cost to US Health Care System in 2011		
	Low	Midpoint	High	Low	Midpoint	High
Failures of care delivery	26	36	45	102	128	154
Failures of care coordination	21	30	39	25	35	45
Overtreatment	67	77	87	158	192	226
Administrative complexity	16	36	56	107	248	389
Pricing failures	36	56	77	84	131	178
Fraud and abuse	30	64	98	82	177	272
Total[c]	**197**	**300**	**402**	**558**	**910**	**1263**

Bad information/decisions

$.3-.4T

[a] Table entries represent the range of estimates of waste in each category from sources cited in the text. The total waste estimates are simply the sums of the category-level estimates. This simple summing is feasible because the categories are defined in such a way that wasteful behaviors could be assigned to at most 1 category and because, like Pacala and Socolow,[9] we did not attempt to estimate interactions between or among the categories.
[b] Including both state and federal costs.
[c] Totals may not match the sum of components due to rounding.

Figure. Proposed "Wedges" Model for US Health Care, With Theoretical Spending Reduction Targets for 6 Categories of Waste



The "wedges" model for US health care follows the approach based on the model by Pacala and Socolow.[9] The solid black "business as usual" line depicts a current projection of health care spending, which is estimated to grow faster than the gross domestic product (GDP), increasing the percentage of GDP spent on health care; the dashed line depicts a more sustainable level of health care spending growth that matches GDP growth, fixing the percentage of GDP spent on health care at 2011 levels. Between these lines lies the "stabilization triangle"—the reduction in national health care expenditures needed to close the gap. The 6 colored regions filling the triangle show one possible set of spending reduction targets; each region represents health care expenditures as a percentage of GDP that could be eliminated by reduction of spending in that waste category over time.

ONLINE FIRST

Eliminating Waste in US Health Care

Donald M. Berwick, MD, MPP
Andrew D. Hackbarth, MPhil

The need is urgent to bring US health care costs into a sustainable range for both public and private payers. Commonly, programs to contain costs use cuts, such as reductions in payment levels, benefit structures, and eligibility. A less harmful strategy would reduce waste, not value-added care. The opportunity is immense. In just 6 categories of waste—overtreatment, failures of care coordination, failures in execution of care processes, administrative complexity, pricing failures, and fraud and abuse—the sum of the lowest available estimates exceeds 20% of total health care expenditures. The actual total may be far greater. The savings potentially achievable from systematic, comprehensive, and cooperative pursuit of even a fractional reduction in waste are far higher than from more direct and blunter cuts in care and coverage. The potential economic dislocations, however, are severe and require mitigation through careful transition strategies.

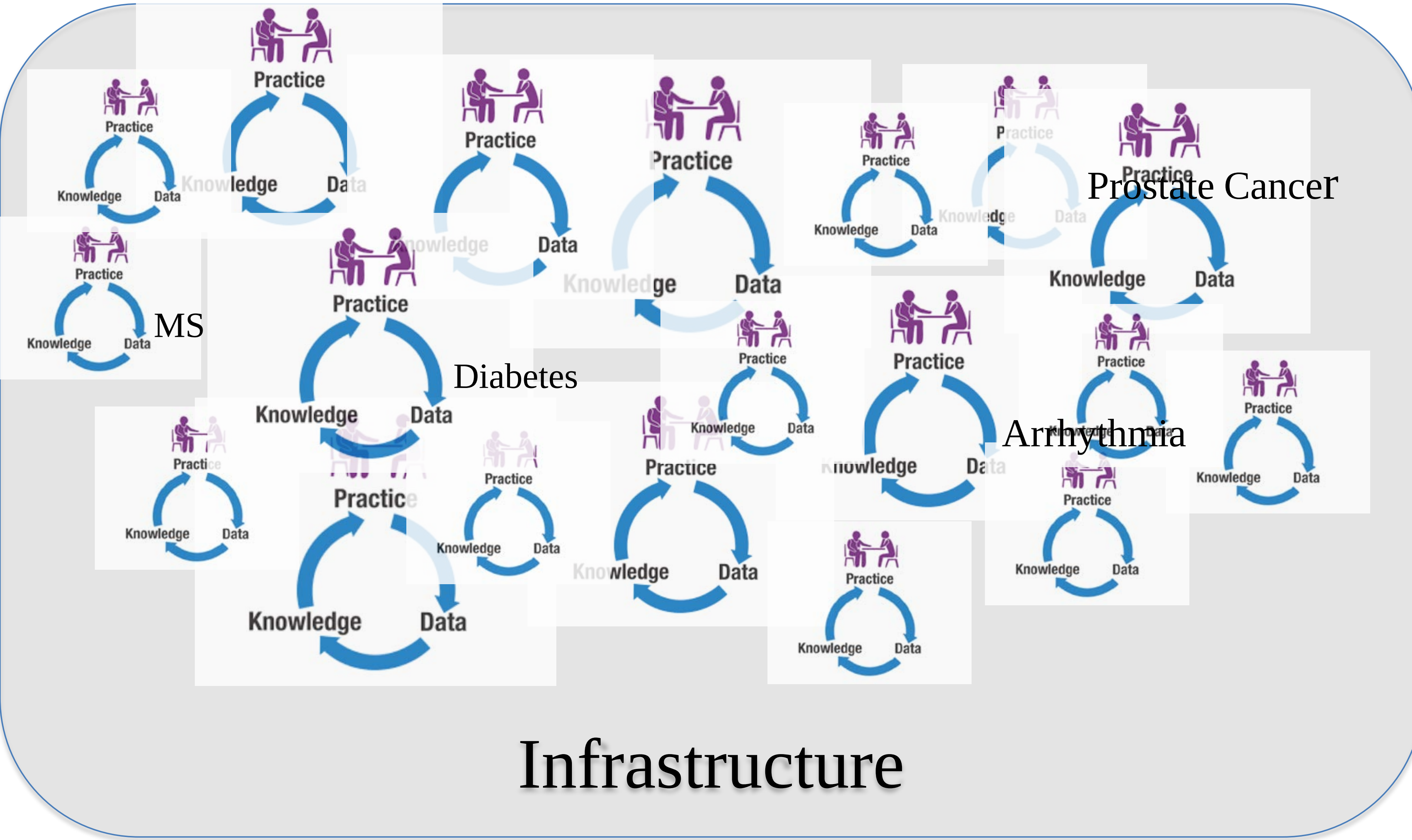
JAMA. 2012;307(14):doi:10.1001/jama.2012.362 www.jama.com

NO MATTER HOW POLARIZED politics in the United States have become, nearly everyone agrees that health care costs are unsustainable. At almost 18% of the gross domestic product (GDP) in 2011, headed for 20% by 2020,[1,2] the nation's increasing health care expenditures reduce the resources available for other worthy government programs, erode wages, and undermine the competitiveness of US industry. Although Medicare and Medicaid are often in the limelight, the health care cost

Short Review

Learning Healthcare System

HealthCare System of Systems Learning



Plato’s Cave

A Role for Biostatistics: *Healthcare Decision Support*
PLAY A CLINICIAN (for a moment)

40 year old man, no family history, tests positive for a life-threatening disease in a routine screen

What is his disease state; what action do you recommend?

Data from prior population of similar people

	True disease status		
Exam result	Yes	No	Total
Positive	15	985	1,000
Negative	5	8,995	9000
Total	20	9,980	10,000

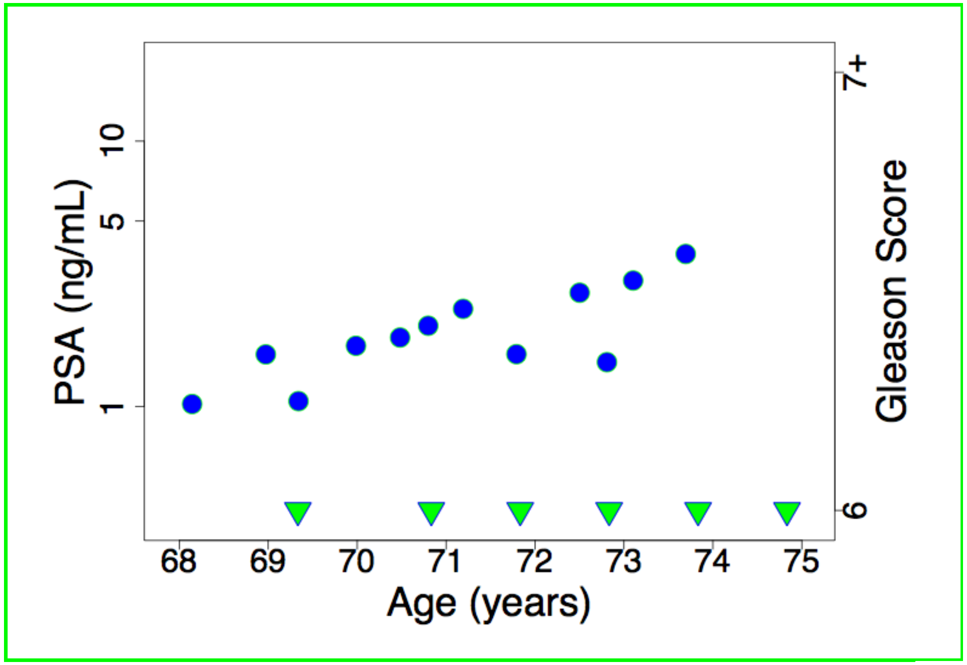
Two Goals for Biostatistics

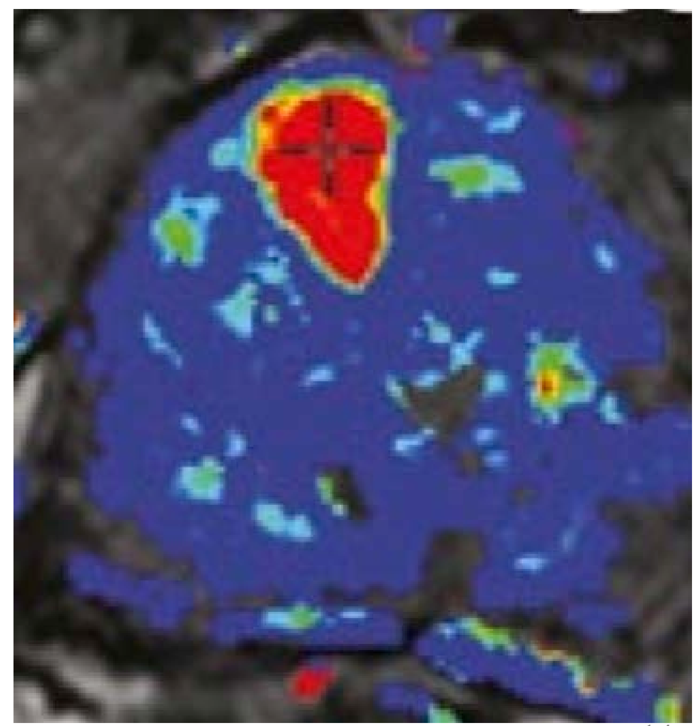
- Create the analogue of the 2x2 table for more complex measurements

Population ⇔ Individual

- Build capacity to make tables for ever narrower sets of "otherwise similar" subgroups of individuals

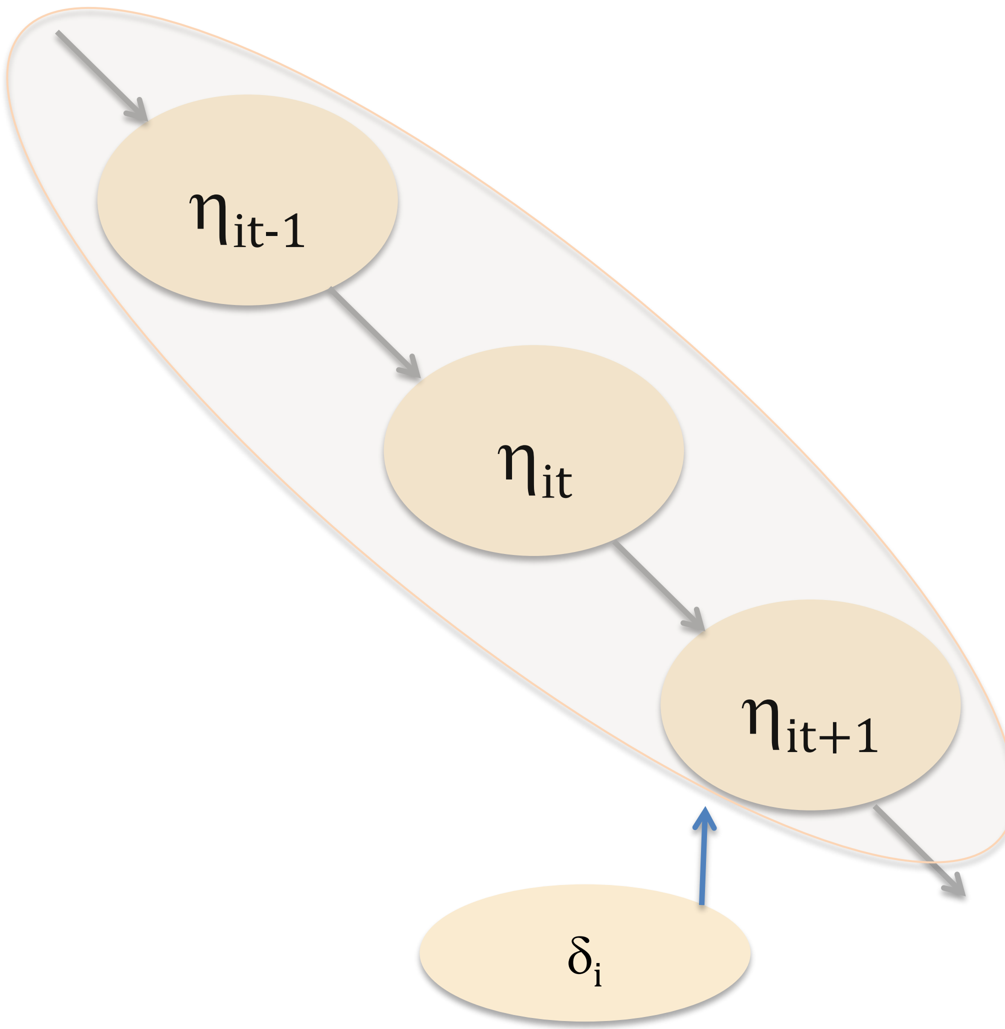
Subset, Subset, Subset



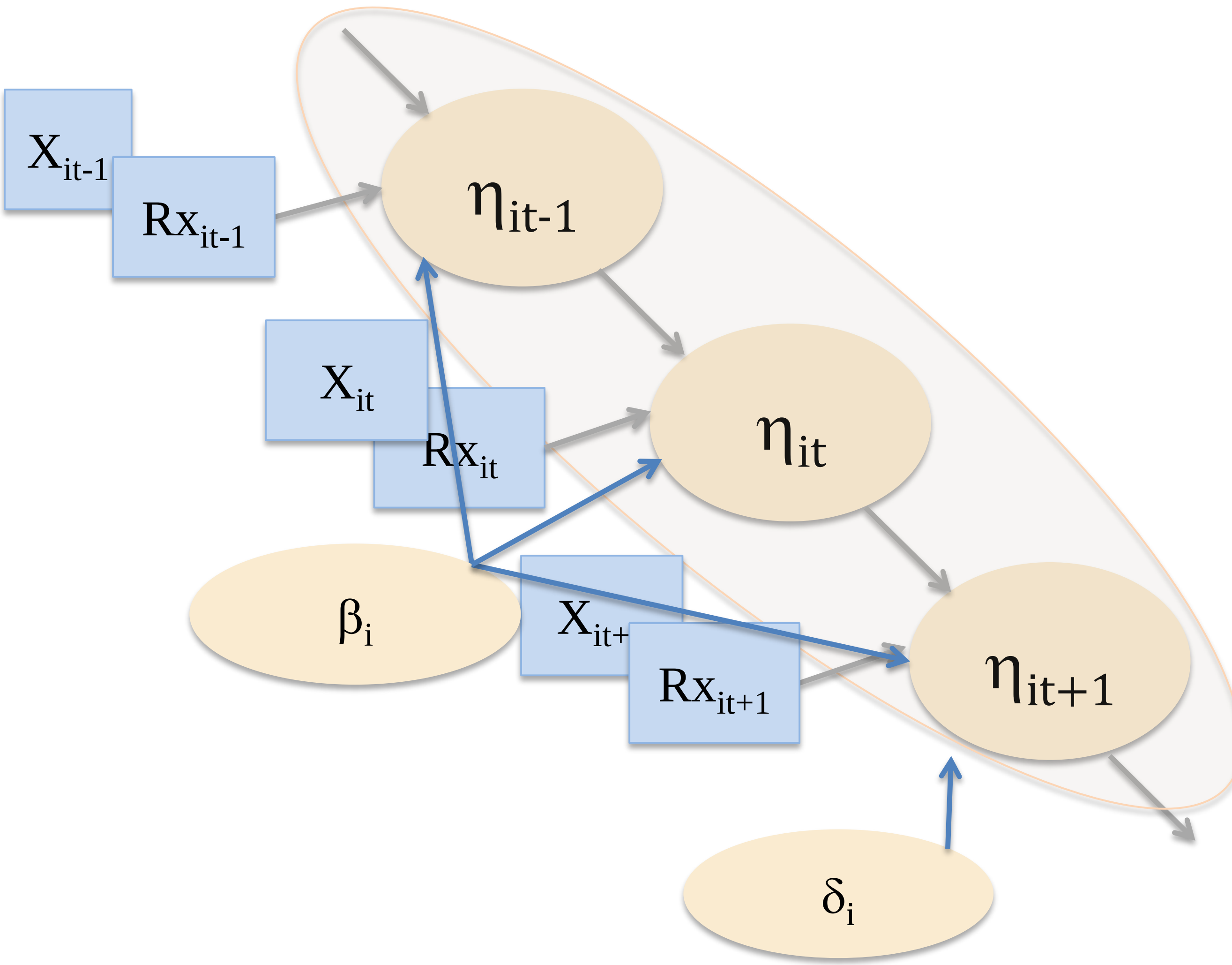


What is this man's chance of having an aggressive tumor?
(a) 1%   (b) 10% (c) 50%
(d) 90% (e) 99%

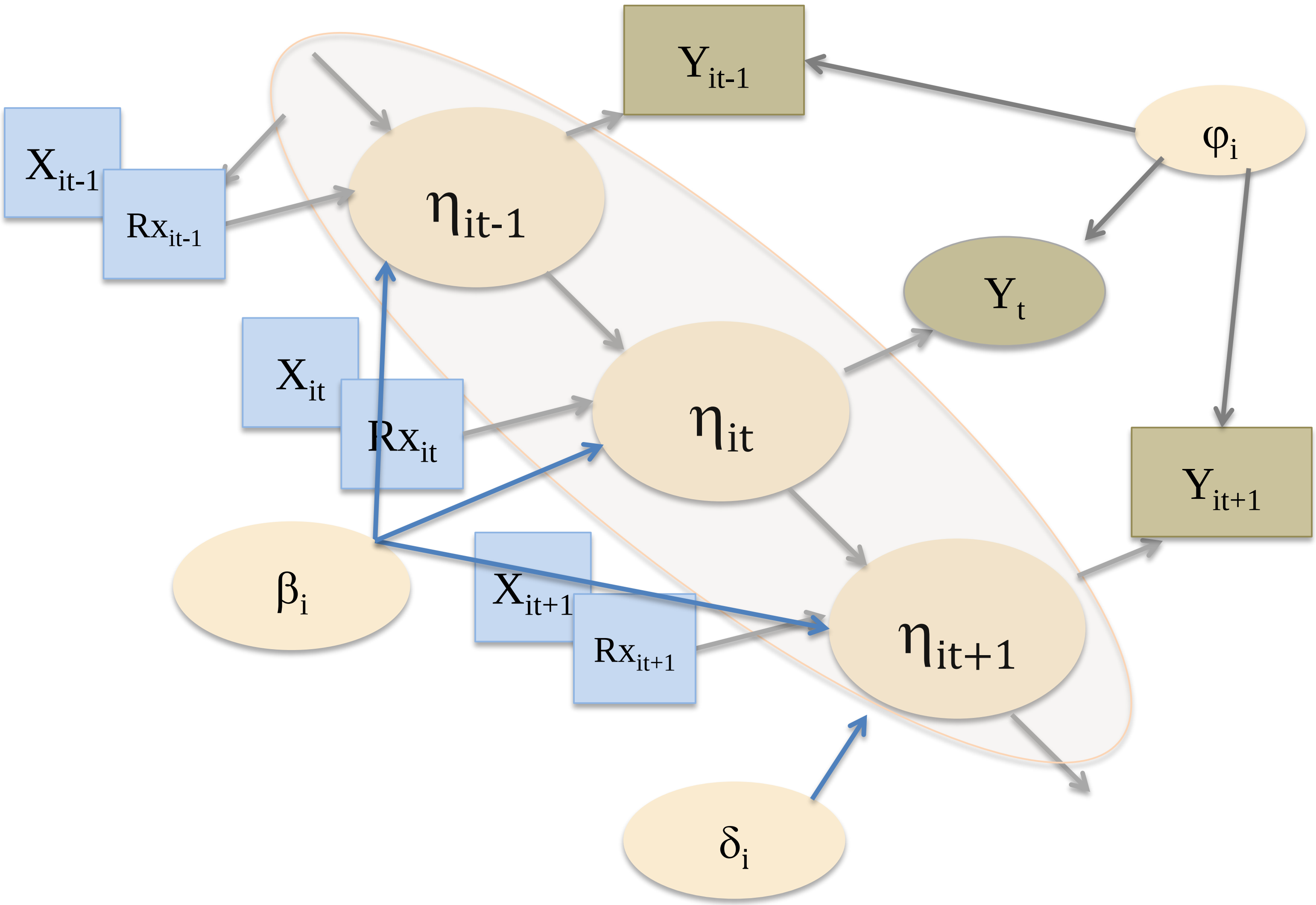
Bayesian Hierarchical Model for Health State/Trajectory (η_{it}) with Person-specific Indicator (δ_i)



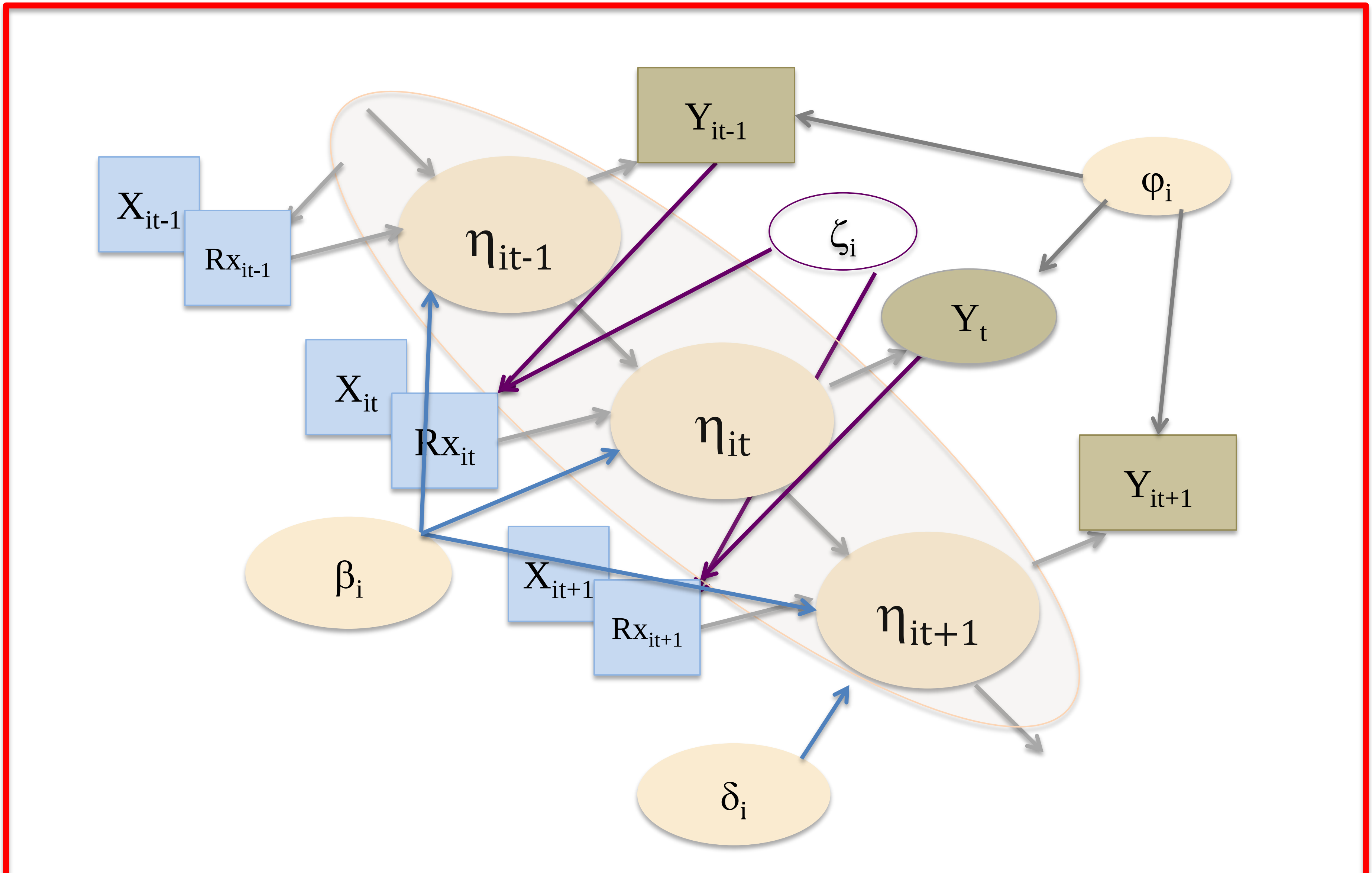
Effects of Exogenous (X) and Endogenous (Rx) Covariates on Health State/Trajectory with Person-specific Regression Coefficients (β_i)

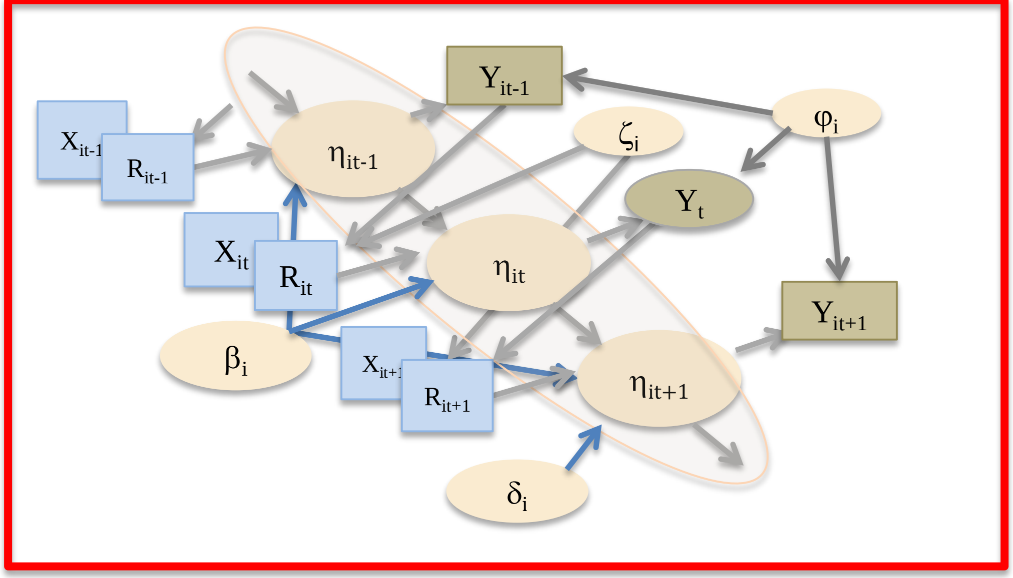


Observations (Y) that Inform about Health State through Coefficients (φ_i)

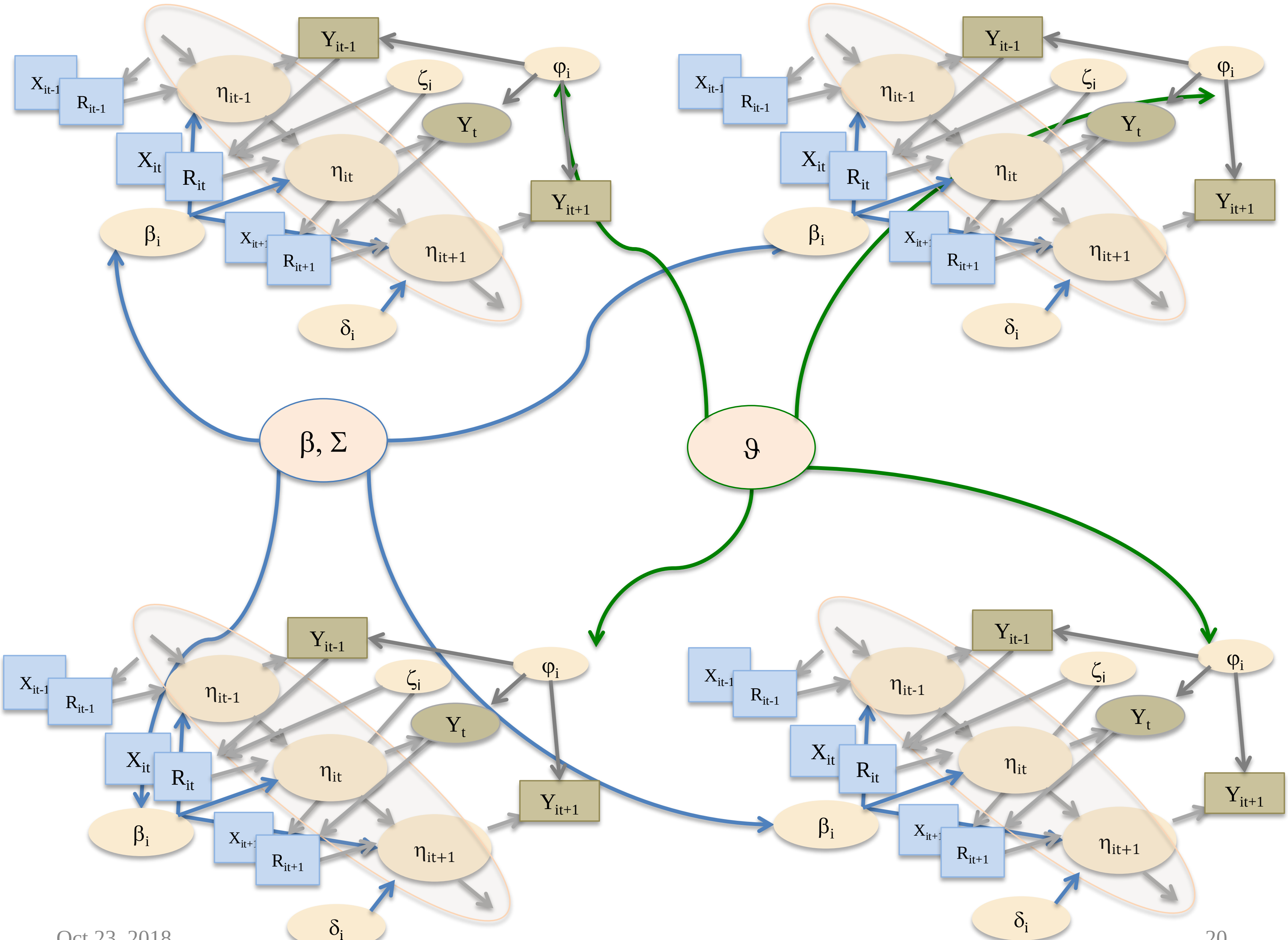


Treatment Decisions Depend on **Past Measured** Outcomes through Parameters (ζ_i)





Y_{it-1}
φ_i
X_{it-1}
R_{it-1}
η_{it-1}
ζ_i
Y_t
X_{it}
R_{it}
η_{it}
Y_{it+1}
β_i
X_{it+1}
R_{it+1}
η_{it+1}
δ_i



β, Σ
ϑ
Y it-1
φi
ζi
X it-1
R it-1
η it-1
Yt
X it
R it
η it
Y it+1
βi
X it+1
R it+1
η it+1
δi

Statistical Comments

- Can be partially identifiable models that require external prior information
- Hypothesis generating models
- Aid in selecting/designing embedded RCTs
- Many call these "Causal" or "Structural Equation" Models when assumptions added
- "Predicting Intervention Effects (π) Models"

What's New (at JHM)

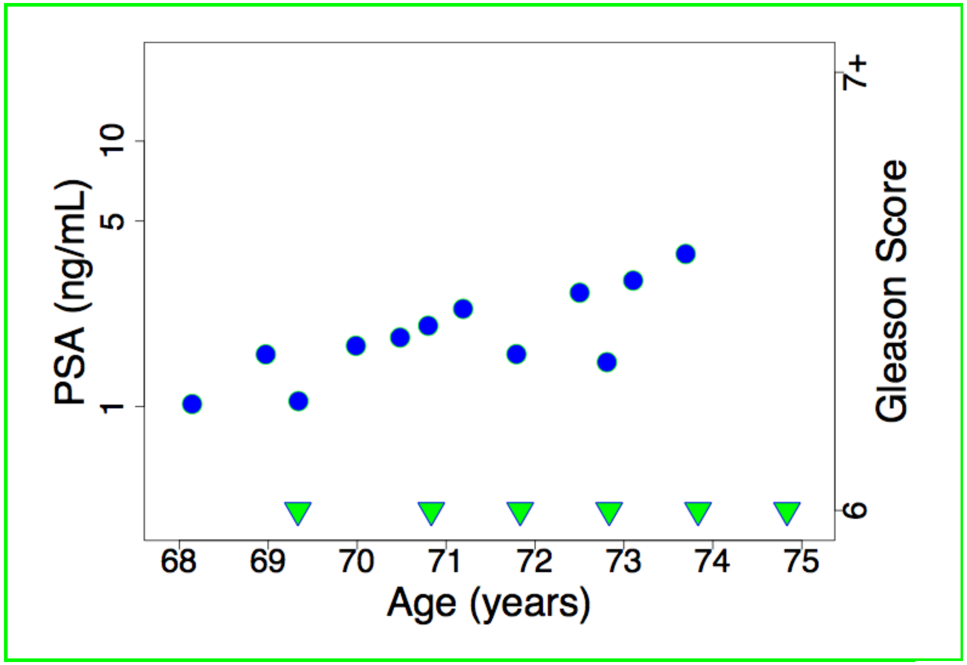
- *in*Health Precision Medicine Centers of Excellence (PMCOEs)
- Precision Medicine Analysis Platform (PMAP)

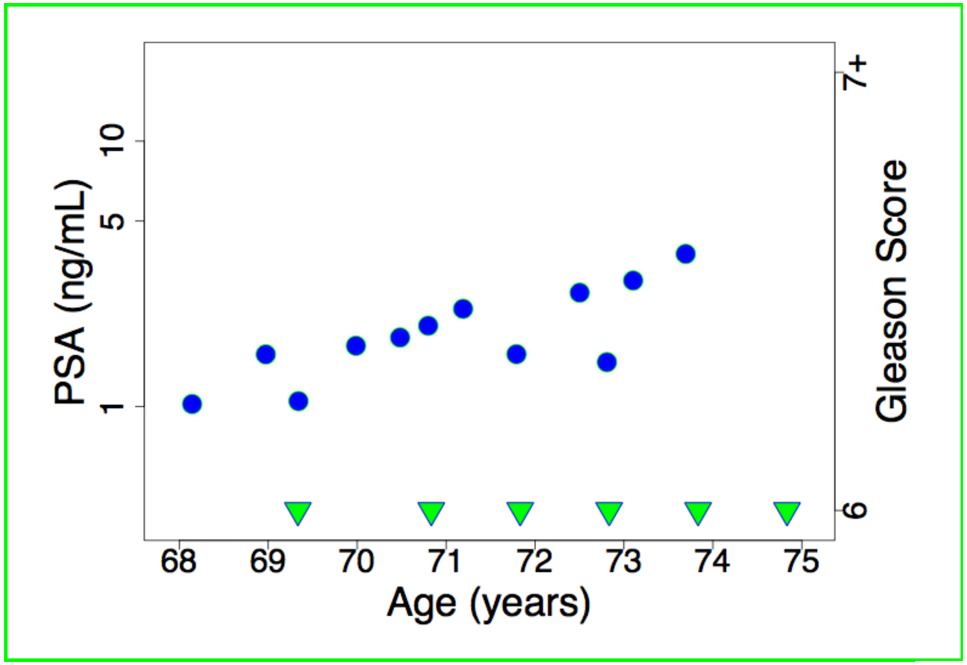
JHM *Precision Medicine Centers of Excellence*
2 => 8 => 30 => ALL

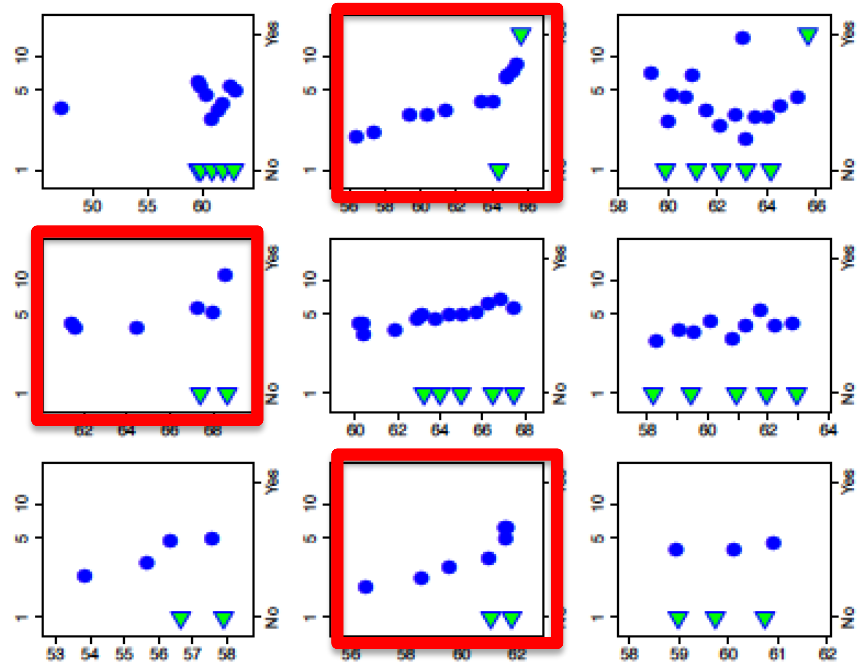
1. Prostate Cancer
2. Multiple Sclerosis
3. Autoimmune Disease (Scleroderma, Myositis,…)
4. Arrhythmia
5. Pancreatic Cancer
6. Bladder Cancer
7. Obesity/Diabetes – JHHC Populations
8. Neurofibromatosis

Prostate Cancer

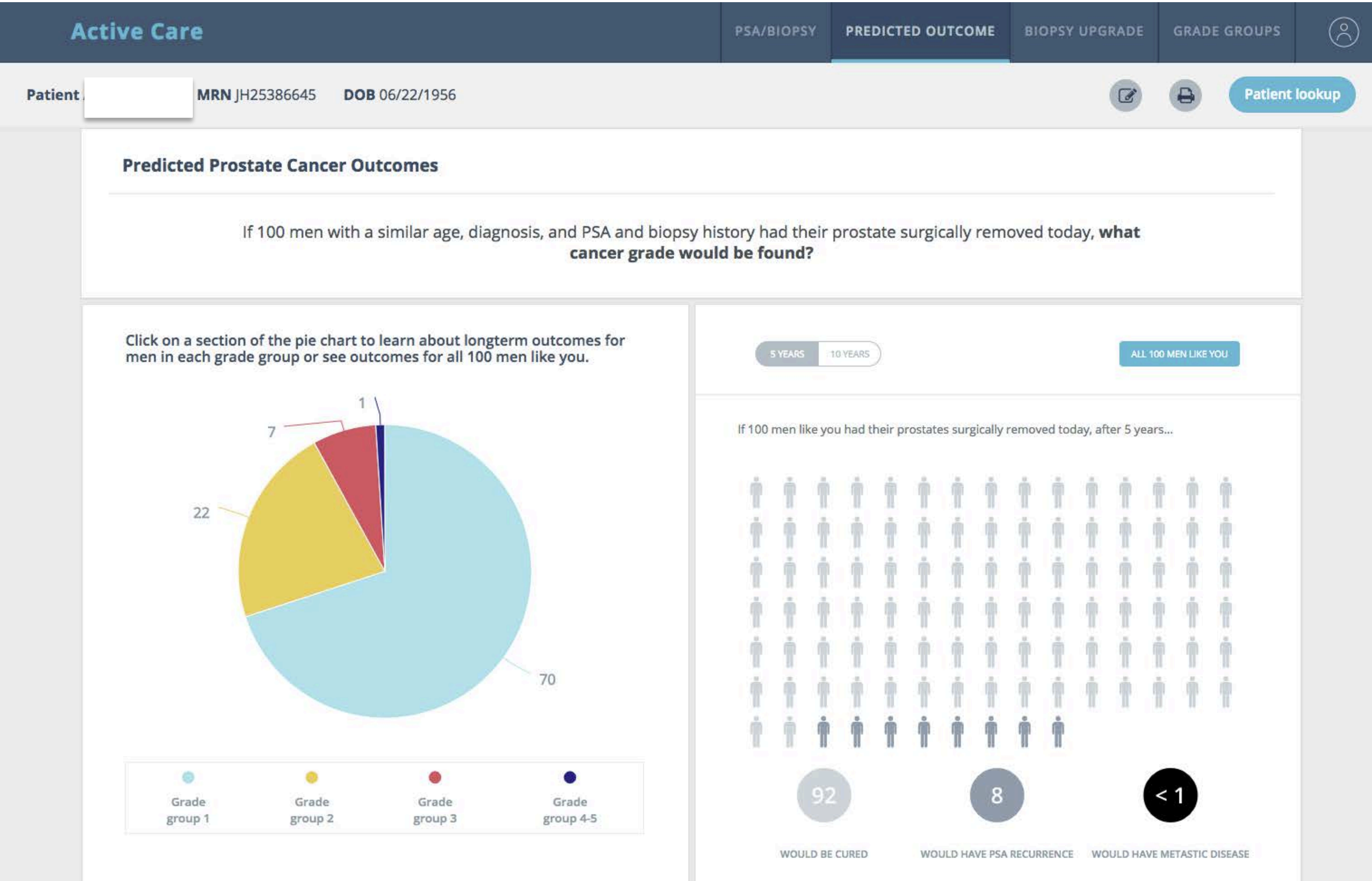
Bal Carter, Yates Coley, Ken Pienta, Mufaddal Mamawala,
Scott Zeger, TIC, APL, IT@JH, JHTV


PSA (ng/mL)
10
5
1
Gleason Score
7+
6
68
69
70
71
72
73
74
75
Age (years)





Pr(Aggressive Tumor) =
8%


Active Care
PSA/BIOPSY
PREDICTED OUTCOME
BIOPSY UPGRADE
GRADE GROUPS
Patient
MRN JH25386645
DOB 06/22/1956
Patient lookup
Predicted Prostate Cancer Outcomes
If 100 men with a similar age, diagnosis, and PSA and biopsy history had their prostate surgically removed today, what cancer grade would be found?
Click on a section of the pie chart to learn about longterm outcomes for men in each grade group or see outcomes for all 100 men like you.
1
7
22
70
Grade group 1
Grade group 2
Grade group 3
Grade group 4-5
5 YEARS
10 YEARS
ALL 100 MEN LIKE YOU
If 100 men like you had their prostates surgically removed today, after 5 years...
92
8
< 1
WOULD BE CURED
WOULD HAVE PSA RECURRENCE
WOULD HAVE METASTIC DISEASE

Steps to Make Healthcare Decisions More Nearly Coherent

Component	Prostate Cancer active surveillance example
• Frame unmet health need	Half of active surveillance prostatectomies yield indolent cancers
• Specify biomedical model	Predictors of indolence: PSA, biopsies, family history, genomic score, MRI
• Wrangle relevant data into a clinical cohort database (CCDB)	Brady Institute, Bal Carter Active Surveillance clinical cohort database with 1300 men; recent collection of genomes, MRIs
• Design and test decision support tool	Coley, et al (a, b): Bayesian hierarchical model
• Design and test users' interface for population health manager, clinician and/or patient	Technology Innovation Center ($300K)
• Design and test on-going curation	JHM Committee
• Devise business model to sustain/improve tool	JHM?
• Scale to nation(s) through consortia	Partners

Bouillabaisse

Boole – a – Bayes

Scaling Models Across Clinics

- Biomedical, clinical and data scientist partnerships in each PMCOE
- IT infrastructure
  – Precision Medicine Analytics Platform (PMAP)
- Scalable strategies, policies, and procedures for more rapid construction of new models
  – Precision Medicine Centers of Excellence (PMCOEs) at JHM
- Business model that rewards science-based, value-producing clinics

Our View

Johns Hopkins Healthcare (JHHC) spends ~$2.5 Billion per year on healthcare for 500,000 members

~ $1 Billion spent per year produces little improvement in health status

So we build statistical models that support coherent decisions that improve outcomes, reduce costs – reinvest a small part of the $1 Billion

Forget JHHC – Think KP

Main Points Once Again

- The Stew
  - The U.S. can no longer waste $1 Trillion per year on healthcare (and continue as a liberal democracy)
  - A large fraction of waste (1/3-1/2) is the result of uncertainty about health state, trajectory and risks/benefits of interventions that is exploited by current perverse incentives
- What's New – Biostatisticians are building models that reduce uncertainty and improve decisions

Our View – just a small part of the $1 trillion wasted be reinvested in changing the American healthcare system

Move over Jeff; Yates in Back

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Thank you