The Value Equation for Assessment of Novel Artificial Intelligence Products in Healthcare

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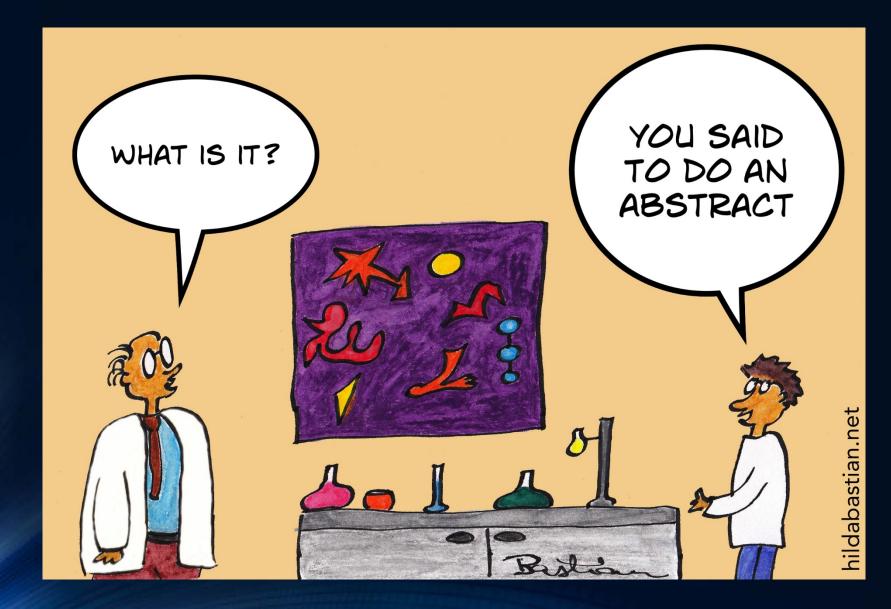
Objectives

To review the definition of `value'

To briefly review approaches to estimating value

 To present 'artificial intelligence' case examples where value assessments can be applied

What is Value?



Defining Value

• Wikipedia: Economic value

 A measure of the benefit that an economic actor can gain from either a good or service

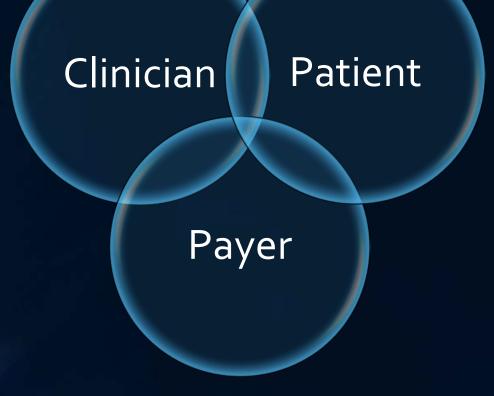
Oxford Dictionary

• The material or monetary worth of something

Health Policy Lay Terminology

 A judgement by a decision-maker on the financial worth of the net benefit of a product or service

Defining Value in Healthcare... Perspectives



Case

An AI tool will soon be available that is expected to significantly reduce mortality by 20% relative to standard care but its licensing costs are considerable. It comes with a significant learning curve for physicians and staff (i.e. not easy to implement) and its false positive rate is higher than desired.

Clinical and economic considerations

Assessing Value: Economic Evaluation

Key Question

• How much will it cost to achieve one unit of 'benefit'?

Traditional economic evaluation

- Cost minimization
- Cost-consequence
- Cost-benefit
- Cost-effectiveness
- Cost-utility

Assessing Value: Economic Evaluation

- Perspective: Who is driving the decision?
 - Perspective will drive the selection of outcomes and costs: payer, patient, society, etc.
- Outcomes
 - Surrogate vs 'hard' outcomes
 - Tangible vs intangible (e.g. quality of life)
- Costs
 - Direct vs indirect
- Time Horizon
 - Short vs long-term

Combining Clinical and Economic Data

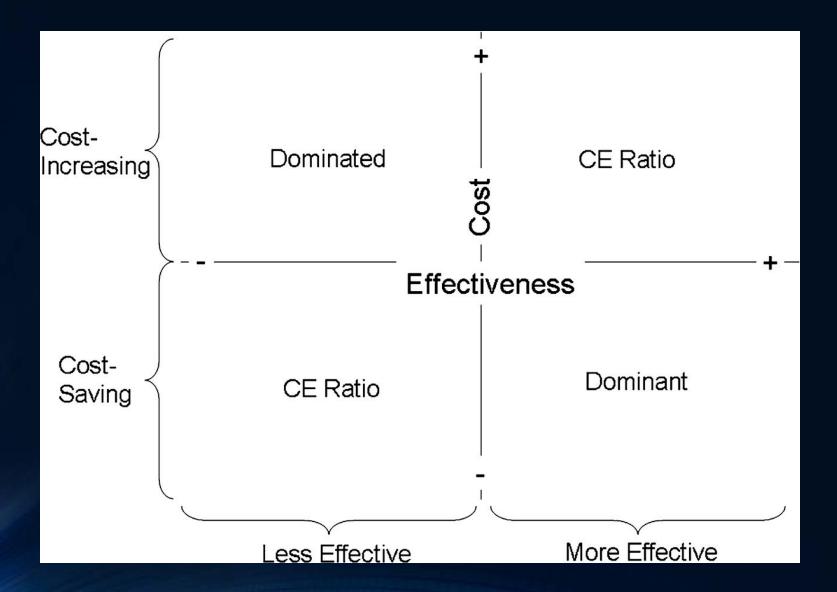
• Usually reflected as a 'cost per quality adjusted life year' by current standards

 Many evaluation groups have 'cost-effectiveness' thresholds for decisionmaking

Cost / QALY = \$50,000 - \$100,000 / quality-adjusted life year

- Implications for Value Assessment (Public Payer): Three critical factors
 - Mortality
 - Healthcare resource utilization (physician visits, ED visits, hospitalizations, etc)
 - Quality of life tools that can map to utility estimates (e.g. SF-36, EQ-5D)

Cost-Effectiveness Grid



Defining Value: Canadian Health Technology Assessment Guidelines

CADTH

CADTH METHODS AND GUIDELINES

Guidelines for the Economic Evaluation of Health Technologies: Canada 4th Edition



Cost Effectiveness

Budget Impact

Assessing Value of AI Products in Healthcare



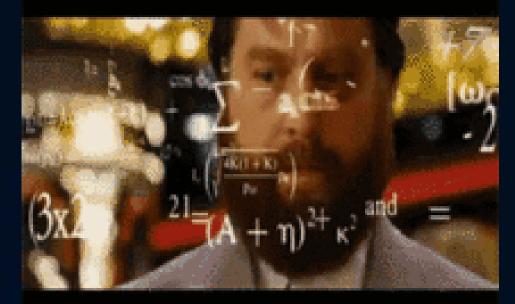
What is Artificial Intelligence??

Google dictionary

 the theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages

How do computers 'learn'??

Data... lots and lots of data Places to store data Ability to process data rapidly



MEMECENTER COM

Unity Health Toronto: St. Michael's Hospital

\$15 million investment

Data warehous

λ Lambda Labs



Collaborations



The Most Advanced Hospital-Based Applied AI Program in Canada

PEOPLE AND CULTURE: THE DSAA TEAM AND COMMUNITY

















































Al at St. Michael's Hospital: Examples

Predicting When Patients Do Poorly

Emergency Department Wait Times

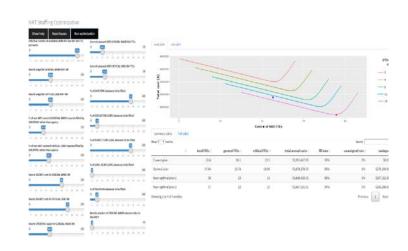
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Forecasting patient volumes 3 days to 3 months in advance

94-96% accuracy ↓ ↓ Wait Times

↑ Quality of Care

Optimizing Nurse Staffing



Optimize Nurse Resource Team Staffing at St. Michael's and St. Joseph's

\$1 million cost reduction annually



↓ Cost

↑ Quality of Care







Predict 24H in Advance: ICU Transfer or Death

> 98% accuracy

↑ Patient Outcomes

Case 1: Optimizing Nurse Staffing

Perspective

• Hospital Administrator

- Cost to build the optimization model
 - About \$30K

- Outcomes
 - Direct costs: total nursing, agency, overtime, nurse resource team
- Value Assessment Approach
 - cost analysis

- Cost impact on nurse staffing
 - Increase in NRT cost agency cost overtime cost
 - About \$1 million reduction annually
- Cost Analysis: net cost reduction / dominant

Case 2: Predicting When Patients Do Poorly

- Perspective
 - Hospital Administrator

- Cost of the prediction model
 - Build: about \$200K
 - Maintenance: about \$10K annually

- Outcomes
 - Mortality: lives saved (est 20% benefit)
 - Quality of life
 - Direct costs: total hospital stay costs (incl. ICU, management costs)

- Cost-Effectiveness
 - Hypothetical: 25 deaths avoided annually with no change in quality of life and no change in total hospital stay costs
 - 1st year C/E: \$8,000/life saved

- Value Assessment Approach
 - Cost-effectiveness or cost-utility analysis

The Hidden Cost of AI: Implementation

Artificial Intelligence is no match for natural stupidity.





Was Implementation Effective? How much did it cost?

What's a 'good' model? How do we 'trust' it?

Unintended Consequences.

Stalenhoef et al. BMC Infectious Diseases (2017) 17:400 DOI 10.1186/s12879-017-2509-3

BMC Infectious Diseases

RESEARCH ARTICLE



(CrossMark

Hospitalization for community-acquired febrile urinary tract infection: validation and impact assessment of a clinical prediction rule

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Abstract

Background: There is a lack of severity assessment tools to identify adults presenting with febrile urinary tract infection (FUTI) at risk for complicated outcome and guide admission policy. We aimed to validate the Prediction Rule for Admission policy in Complicated urinary Tract InfeCtion LEiden (PRACTICE), a modified form of the *pneumonia severity index*, and to subsequentially assess its use in clinical practice.

Methods: A prospective observational multicenter study for model validation (2004–2009), followed by a multicenter controlled clinical trial with stepped wedge cluster-randomization for impact assessment (2010–2014), with a follow up of 3 months. Paricipants were 1157 consecutive patients with a presumptive diagnosis of acute febrile UTI (787 in validation cohort and 370 in the randomized trial), enrolled at emergency departments of 7 hospitals and 35 primary care centers in the Netherlands.

The clinical prediction rule contained 12 predictors of complicated course. In the randomized trial the PRACTICE included guidance on hospitalization for high risk (>100 points) and home discharge for low risk patients (<75 points), in the control period the standard policy regarding hospital admission was applied. Main outcomes were effectiveness of the clinical prediction rule, as measured by primary hospital admission rate, and its safety, as measured by the rate of low-risk patients who needed to be hospitalized for FUTI after initial home-based treatment, and 30-day mortality.

Results: A total of 370 patients were included in the randomized trial, 237 in the control period and 133 in the intervention period. Use of PRACTICE significantly reduced the primary hospitalization rate (from 219/237, 92%, in the control group to 96/133, 72%, in the intervention group, p < 0.01). The secondary hospital admission rate after initial outpatient treatment was 6% in control patients and 27% in intervention patients (1/17 and 10/37; p < 0.001).

Legal / ethical considerations: liability associated with using / not using AI.

Questions / Discussion

