THE POWER OF OPPORTUNISTIC FINDINGS USING AI

THE VALUE PERSPECTIVE

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Assistant professor Value-based imaging

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DISCLOSURES

- Medical advisor Noaber Foundation
- Medical advisor NLC
- Medical advisor Contextflow
- Medical advisor Quibim
- Research / travel grant Qure.ai

IMPACT

- Overall opinion medical imaging AI is positive
- High proportion of radiologists believe in positive impact
- Strategic AI-enabled could help in early intervention by getting more patients on the treatment pathway sooner (e.g. heart failure, lung cancer, COPD)

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An evaluation of information online on artificial intelligence in medical imaging

Philip Mulryan, Naomi Ni Chleirigh, Alexander T. O'Mahony, Claire Crowley, David Ryan, Patrick McLaughlin, Mark McEntee, Michael Maher & Owen J. O'Connor

Insights into Imaging **13**, Article number: 79 (2022) | Cite this article

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EVALUATION

MOCK SCORING RUBRIC

Local Performance Metrics/ Ease of Use

0 – Poor local performance, cumbersome UX
10 – Modest local performance, useable UX
20 – Good local performance, good UX
30 – Excellent local performance, excellent UX

Technical Readiness / Workflow Impact

0 – No existing technical infrastructure
10 – Major technical modification
20 – Minor technical modification
30 – All technical infrastructure in place

Scientific Evidence

0 – none / pilot data
10 – Level III/IV limited cohort
20 – Level II prospective clinical evaluation
30 – Level I evidence for primary outcome

Value

0 – Costs unknown
5 – Net negative
10 – Net neutral
15 – Billing code

Fairness/Bias/Harm

0 – unknown
10 – High
20 – Moderate
30 – Lowest risk

Clinical Impact

0 – Low volume low acuity
10 – Moderate volume or moderate acuity
20 – High volume or high acuity
30 – High volume and high acuity

Daye et al, Implementation of Clinical Artificial Intelligence in Radiology: Who Decides and How?; Radiology August 2022
https://pubs.rsna.org/doi/full/10.1148/radiol.212151

EVALUATION

Scientific evidence

- Standard metrics include:
  - Area under the receiver operating characteristic curve; sensitivity and specificity; the precision-recall curve; and, when applicable, regression metrics (root mean square error, mean absolute error, R^2)

- Guidelines have been published for evaluating and reporting the results of AI models:
  - Transparent Reporting of a Multivariable Prediction Model of Individual Prognosis or Diagnosis (TRIPOD-AI)
  - Standards for Reporting of Diagnostic Accuracy Studies (known as STARD-AI)
  - Consolidation Standards of Reporting Trials (known as CONSORT-AI)

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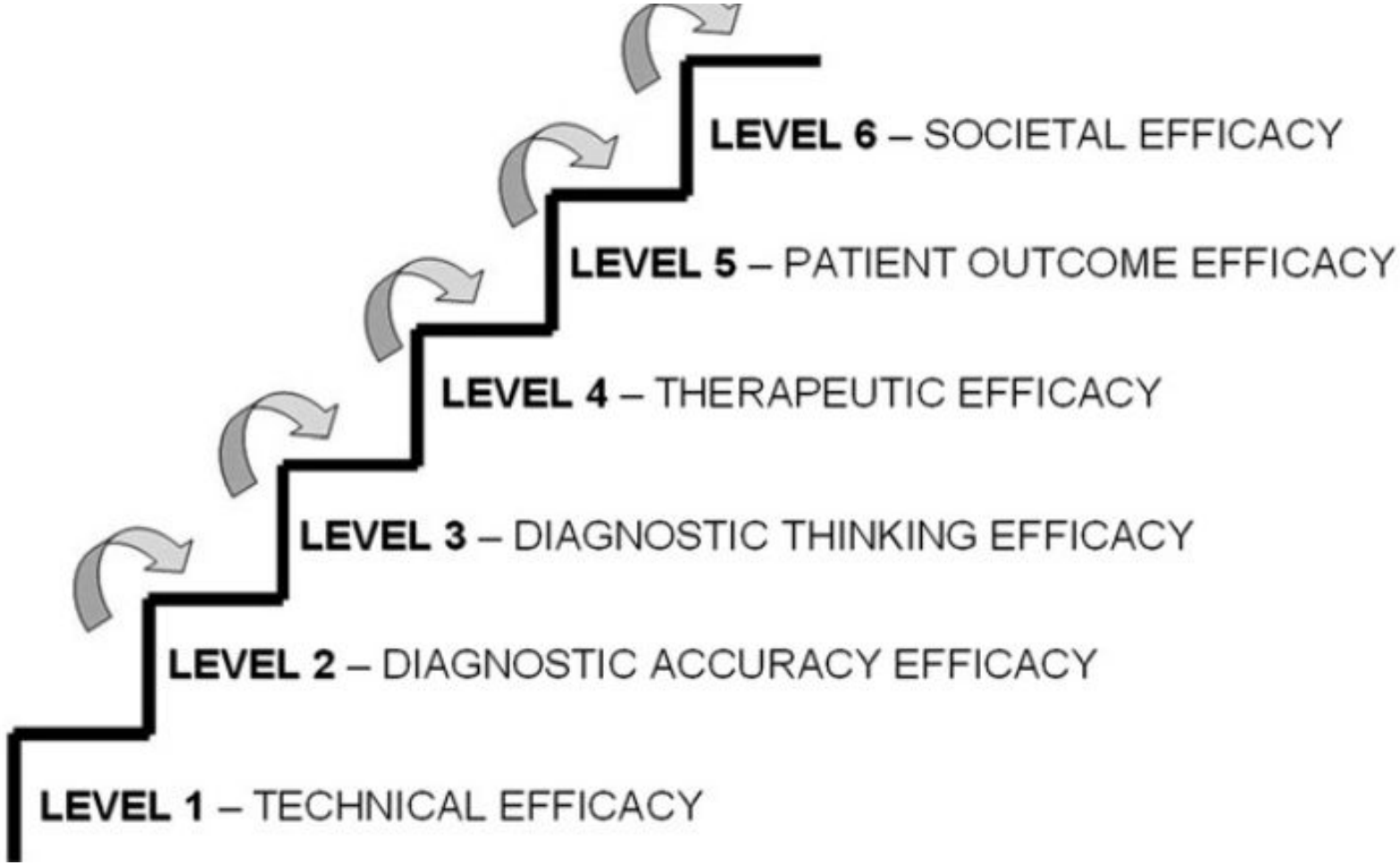
EVALUATION

Scientific evidence

- Fryback model

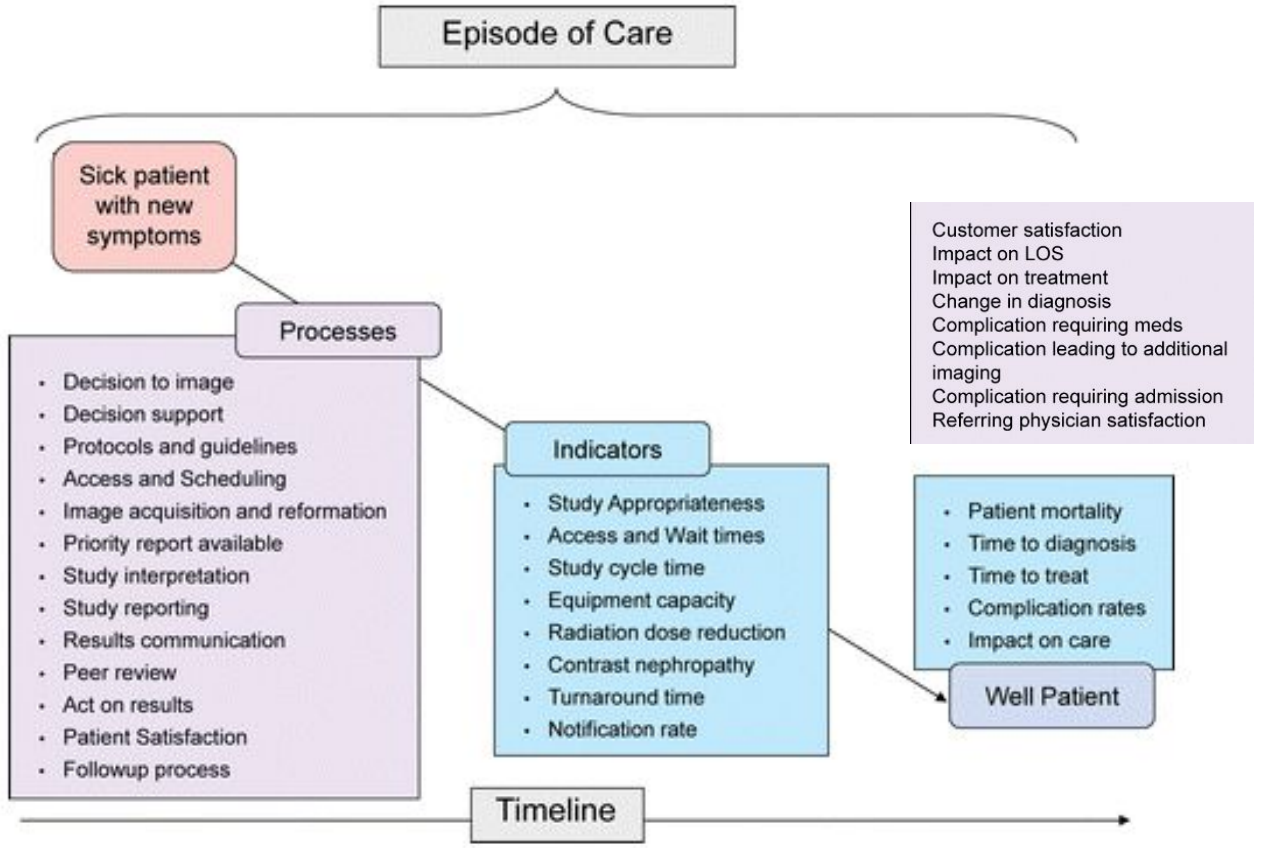


Fryback DG, Thornbury JR. The efficacy of diagnostic imaging. Med Decis Making. 1991 Apr-Jun;11(2):88-94. doi: 10.1177/0272989X9101100203. PMID: 1907710.

EVALUATION

Clinical impact

- Distinguish between:
  - Process metrics
  - Outcomes metrics
  - Value metrics

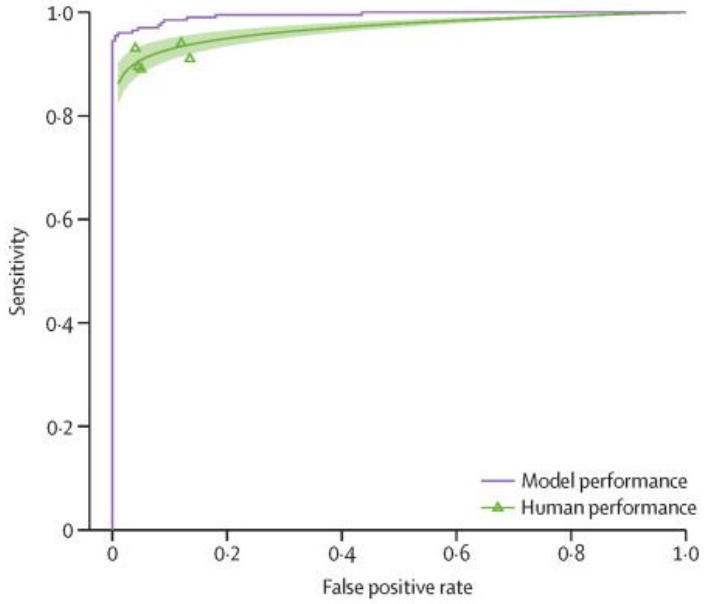


Sarwar A, Boland G, Monks A, Kruskal JB. Metrics for Radiologists in the Era of Value-based Health Care Delivery. Radiographics. 2015 May-Jun;35(3):866-76. doi: 10.1148/rg.2015140221. Epub 2015 Apr 3. PMID: 25839737.

EVALUATION

Local situation

- Most deep learning algorithms show fall in accuracy in external datasets
- Lack of diverse datasets in AI research puts patients at risk
  - Algorithm detecting proximal femoral fractures
  - Model outperformed humans
    - Operating point needed to change in external validation set
    - Unexpected and potentially harmful algorithm behavior (abnormal bones)



Oakden-Rayner L, Gale W, Bonham TA, Lungren MP, Carneiro G, Bradley AP, Palmer LJ. Validation and algorithmic audit of a deep learning system for the detection of proximal femoral fractures in patients in the emergency department: a diagnostic accuracy study. Lancet Digit Health. 2022 May;4(5):e351-e358. doi: 10.1016/S2589-7500(22)00004-8. Epub 2022 Apr 5. PMID: 35396184.

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EVALUATION

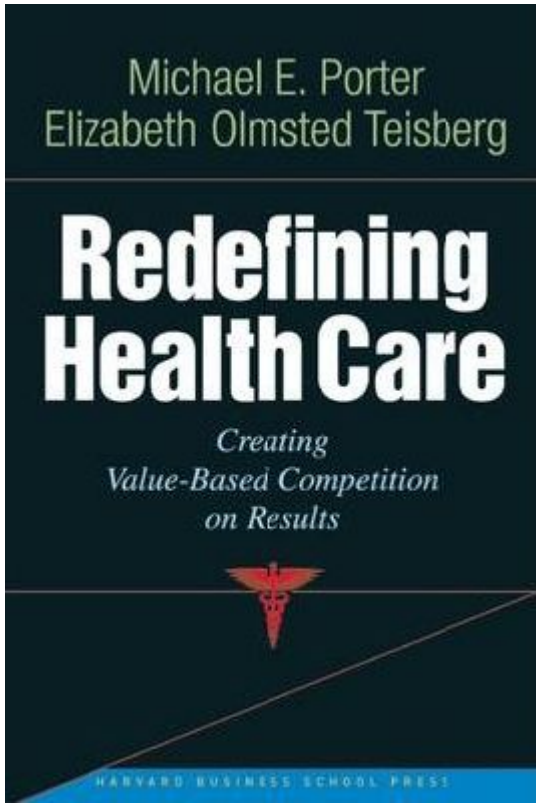
Local situation

- Data set used for model development congruent with setting in which model will be used
  - In- and exclusion criteria applied
- Unbiased local dataset:
  - Accuracy and reproducability
    - > Sensitivity / specificity versus clinical utility thresholds
- Identify effects along health care chain
- Technical / workflow impact

Trivedi H. The Business of Artificial Intelligence in Radiology Has Little to Do With Radiologists. J Am Coll Radiol. 2022 Apr;19(4):564-566. doi: 10.1016/j.jacr.2022.01.006. Epub 2022 Feb 15. PMID: 35176248.

EVALUATION

Value



$$\text{Patient Value} = \frac{\text{Health Outcomes}}{\text{Cost}}$$

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EVALUATION

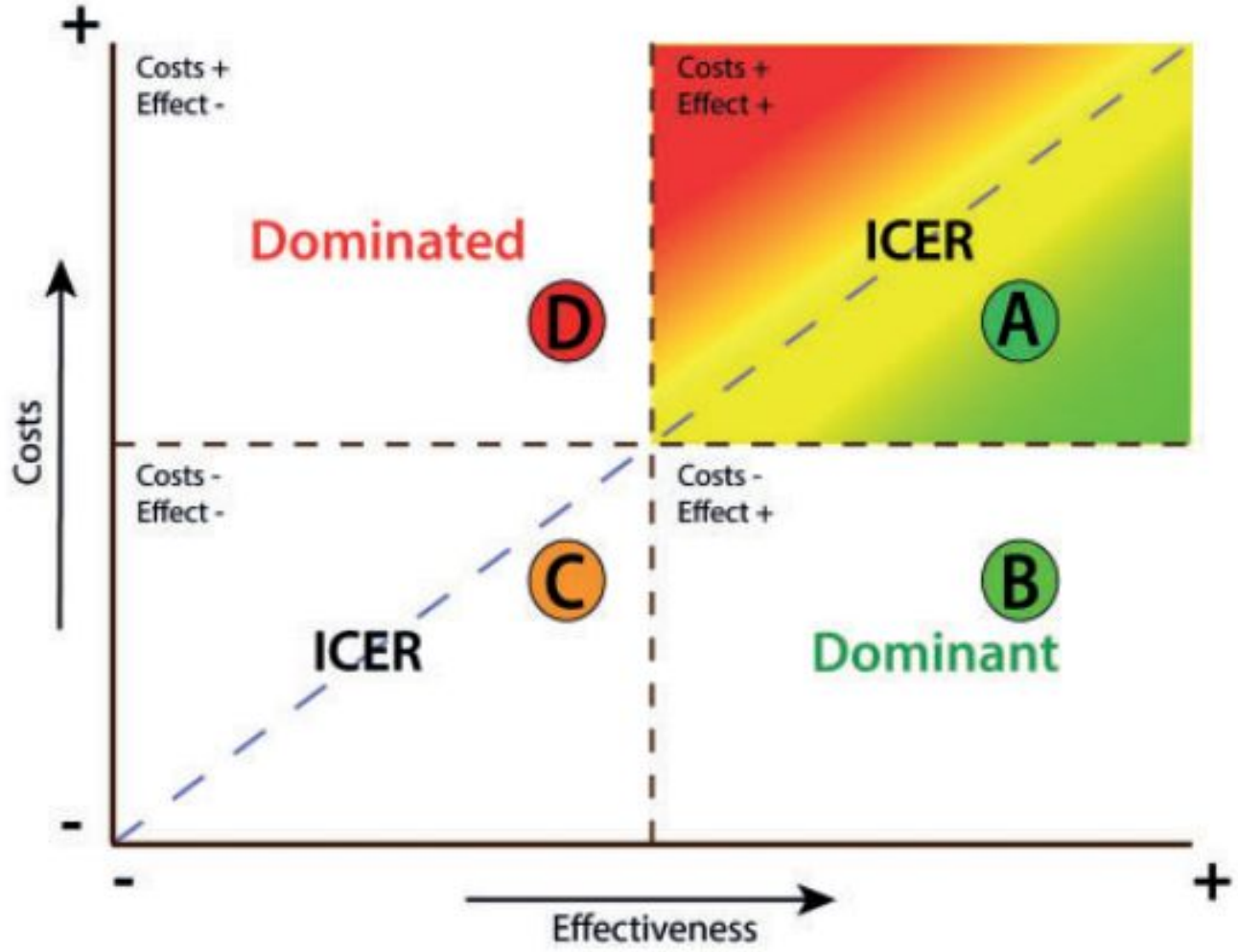
Value

Cost-effectiveness analysis	Value-based healthcare
$ICER = \frac{Costs\ (A\text{-}B)}{Outcomes\ (A\text{-}B)}$	$Value = \frac{Outcomes}{Costs}$

ICER indicates incremental cost-effectiveness ratio.

EVALUATION

Value



Antonides CFJ, Cohen DJ, Osnabrugge RLJ. Statistical primer: a cost-effectiveness analysis. Eur J Cardiothorac Surg. 2018 Aug 1;54(2):209-213. doi: 10.1093/ejcts/ezy187. PMID: 29726940.

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CONCLUSIONS

- Scientific evidence
  - Standard metrics
  - 6-level Fryback model
- Clinical impact
  - Process vs outcome vs value metrics
- Thorough evaluation needed of AI-algorithms before implementation
  - Local performance metrics
    - Hospital / region / country
    - Consider whole health care chain
- Value
  - Need to consider costs along health care chain
  - Combine cost-effectiveness analysis and value-based healthcare


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