Kan AI en big data ons aan verantwoordbare zorg helpen?

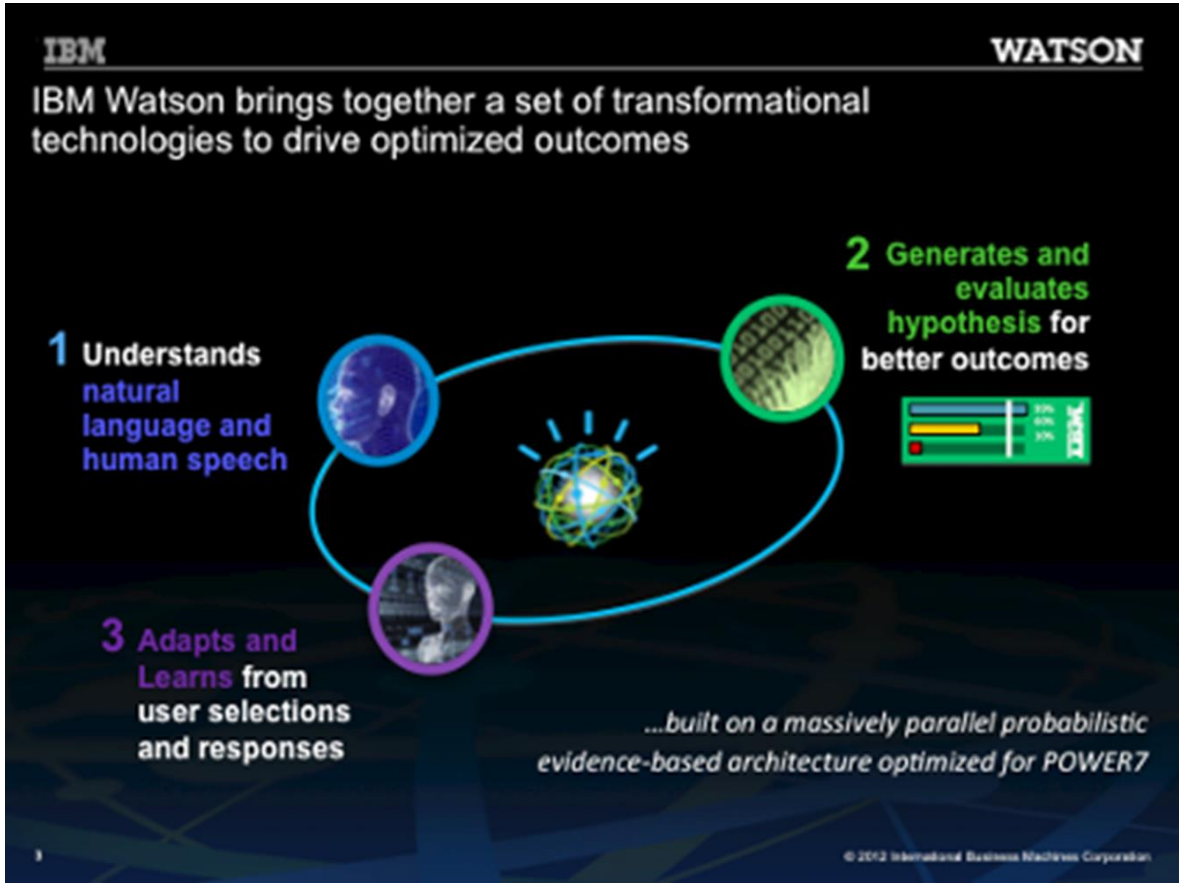
Prof. Dr. W. Van Biesen
Ghent University Hospital

Annals of Internal Medicine   PRECISION MEDICINE

Cases in Precision Medicine: Genetic Assessment After a Sudden Cardiac Death in the Family

Ronald Laracuente, BA; Marc Paul Waase, MD; Isha Kalia, MS; Arthur A.M. Wilde, MD; and Wendy K. Chung, MD, PhD

Sudden death in a family is associated with serious anxiety … made, relatives should receive genetic testing and clinical as-

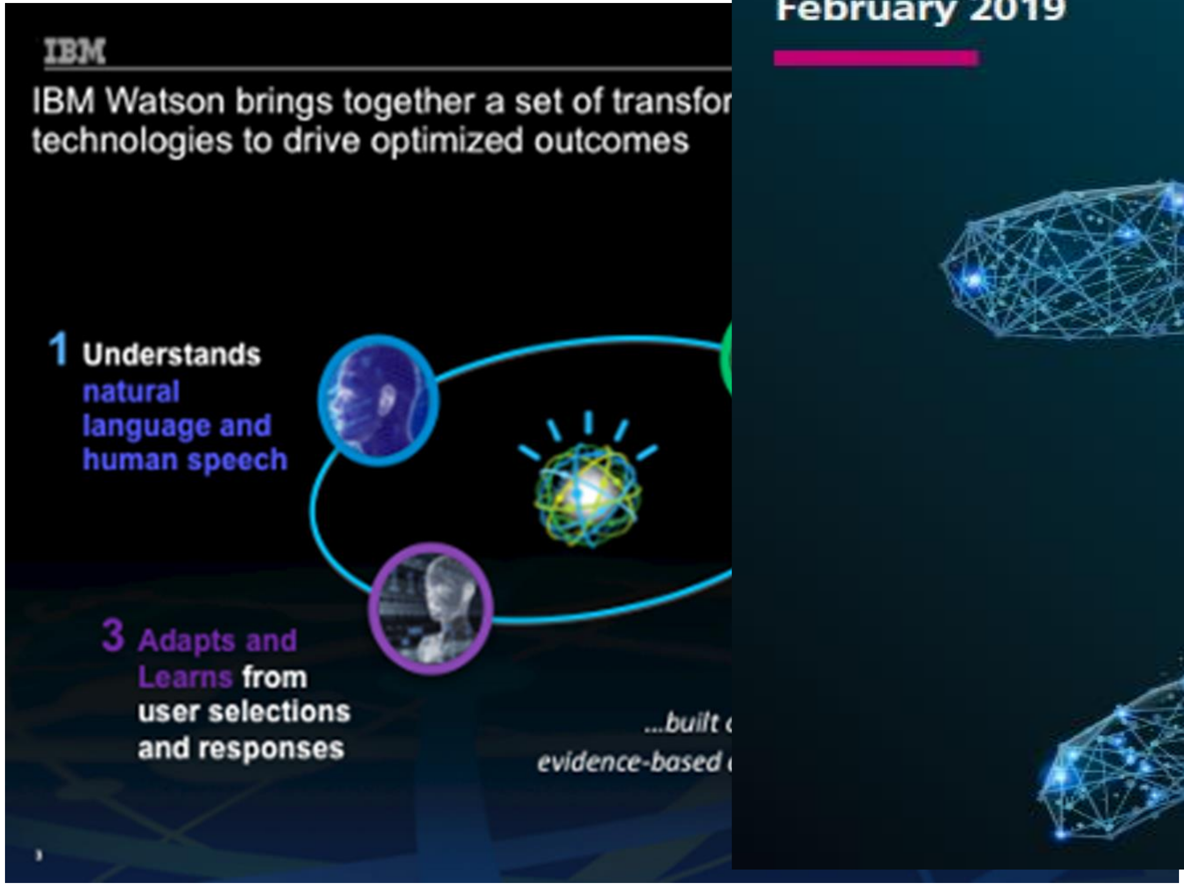


Annals of Internal Medicine

Cases in Precision Medicine: Genetic As
Cardiac Death in the Family

Ronald Laracuente, BA; Marc Paul Waase, MD; Isha Kalia, MS; Arthur A.M

Sudden death in a family is associated with serious anxiety mad



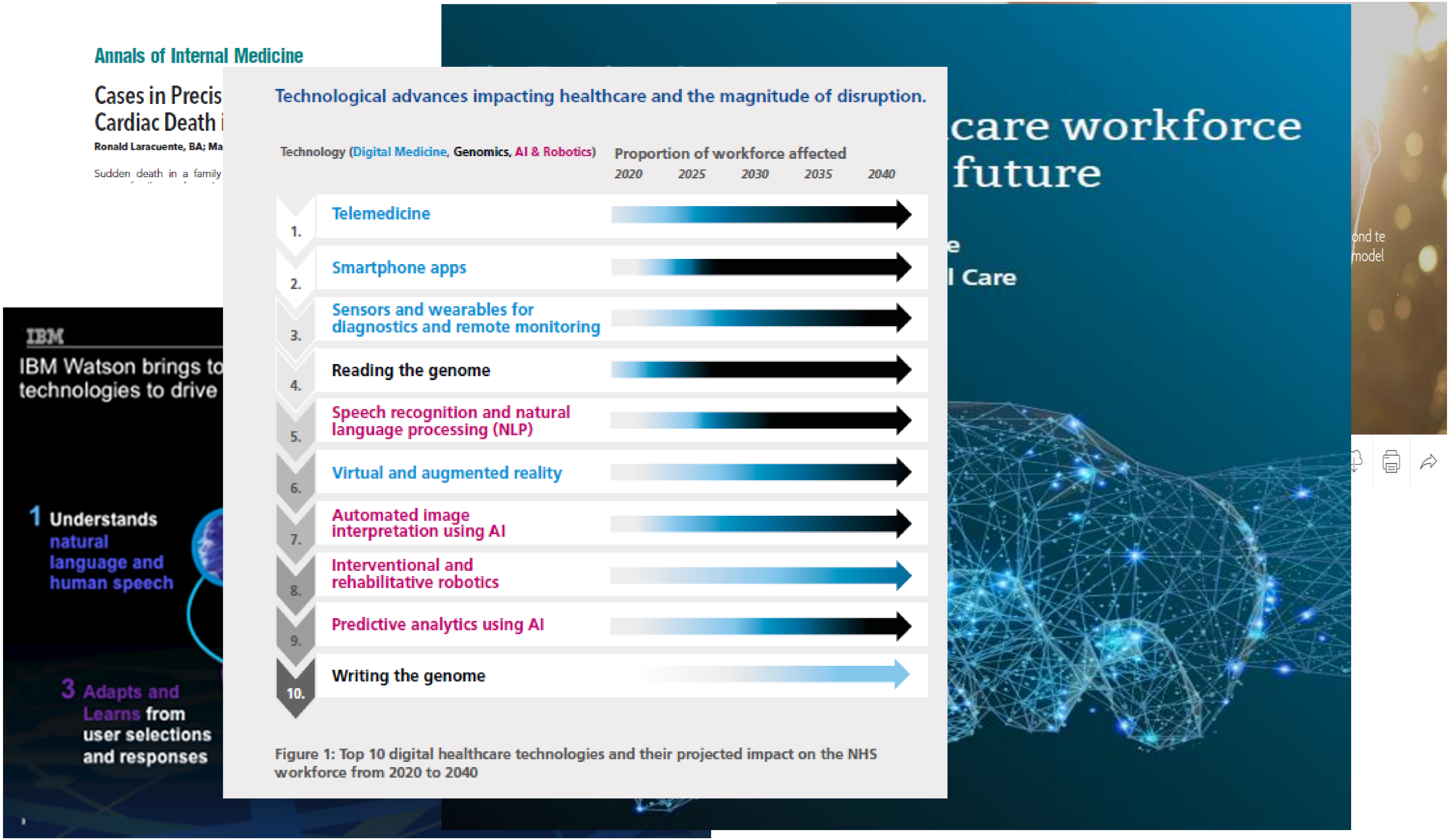
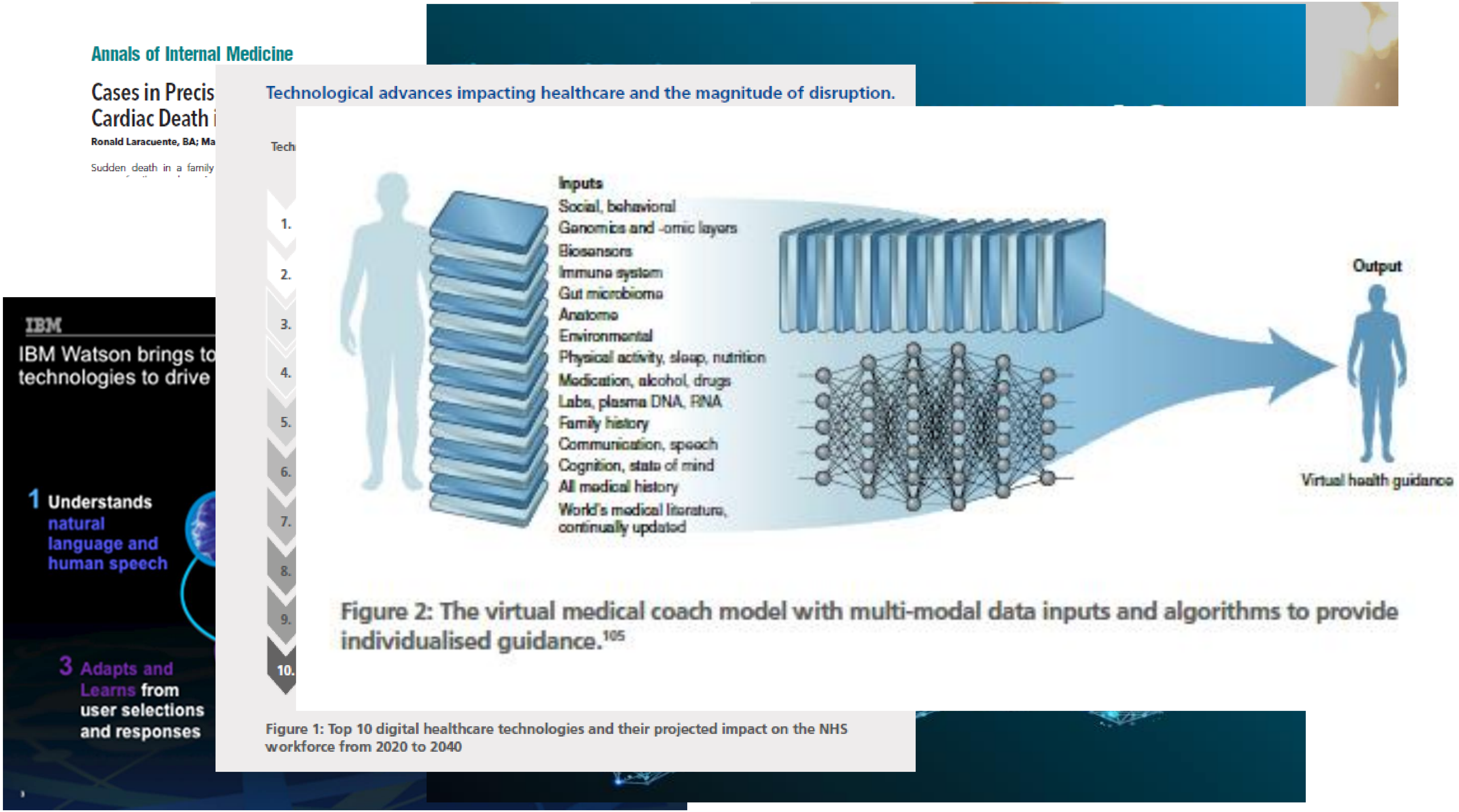
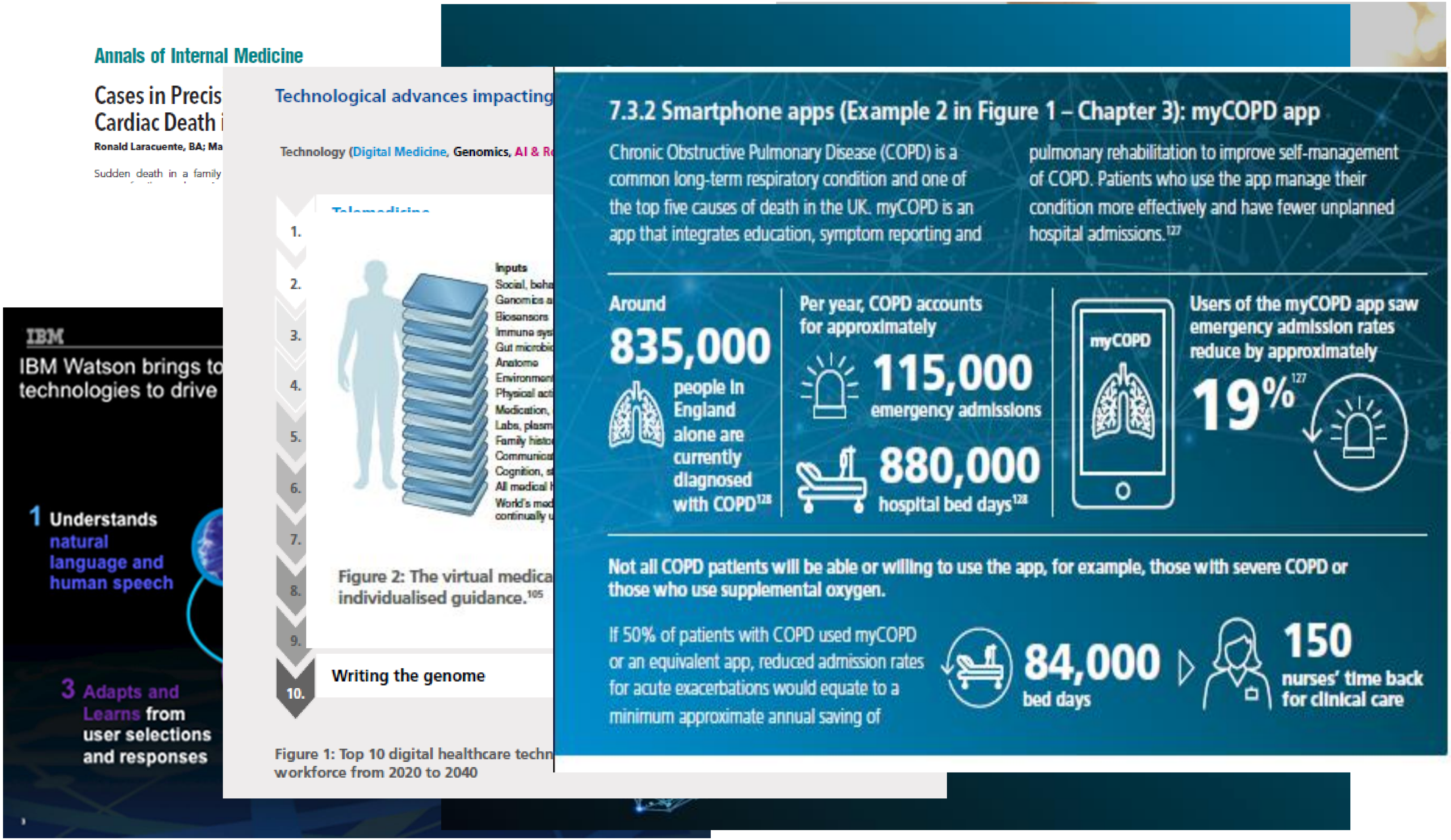
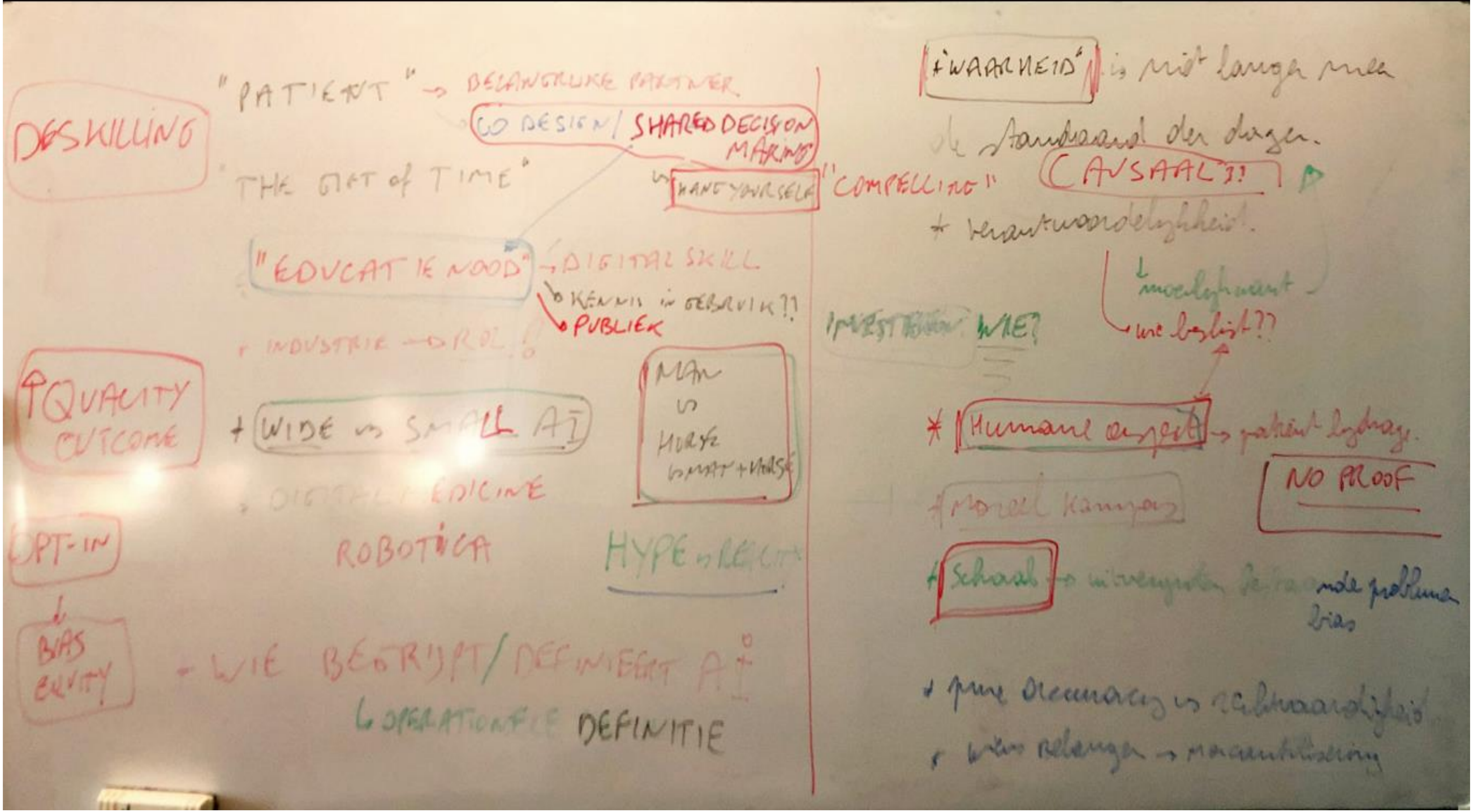


Figure 1: Top 10 digital healthcare technologies and their projected impact on the NHS workforce from 2020 to 2040


Annals of Internal Medicine
Cases in Precis
Cardiac Death i
Ronald Laracuente, BA; Ma
Sudden death in a family
IBM
IBM Watson brings to
technologies to drive
1 Understands natural language and human speech
3 Adapts and Learns from user selections and responses
Technological advances impacting healthcare and the magnitude of disruption.
1.
2.
3.
4.
5.
6.
7.
8.
9.
10.
Figure 1: Top 10 digital healthcare technologies and their projected impact on the NHS workforce from 2020 to 2040
Inputs
Social, behavioral
Genomics and -omic layers
Biosensors
Immune system
Gut microbiome
Anatome
Environmental
Physical activity, sleep, nutrition
Medication, alcohol, drugs
Labs, plasma DNA, RNA
Family history
Communication, speech
Cognition, state of mind
All medical history
World's medical literature, continually updated
Output
Virtual health guidance
Figure 2: The virtual medical coach model with multi-modal data inputs and algorithms to provide individualised guidance.105



Annals of Internal Medicine
Cases in Precis
Cardiac Death i
Ronald Laracuente, BA; Ma
Sudden death in a family
IBM
IBM Watson brings to
technologies to drive
1 Understands natural language and human speech
3 Adapts and Learns from user selections and responses
Technological advances impacting
Technology (Digital Medicine, Genomics, AI & R
1.
2.
3.
4.
5.
6.
7.
8.
9.
10.
Writing the genome
Inputs
Figure 2: The virtual medica
individualised guidance.[105]
Figure 1: Top 10 digital healthcare techn
workforce from 2020 to 2040
7.3.2 Smartphone apps (Example 2 in Figure 1 – Chapter 3): myCOPD app
Chronic Obstructive Pulmonary Disease (COPD) is a common long-term respiratory condition and one of the top five causes of death in the UK. myCOPD is an app that integrates education, symptom reporting and pulmonary rehabilitation to improve self-management of COPD. Patients who use the app manage their condition more effectively and have fewer unplanned hospital admissions.[127]
Around
835,000
people in England alone are currently diagnosed with COPD[128]
Per year, COPD accounts for approximately
115,000
emergency admissions
880,000
hospital bed days[128]
myCOPD
Users of the myCOPD app saw emergency admission rates reduce by approximately
19%[127]
Not all COPD patients will be able or willing to use the app, for example, those with severe COPD or those who use supplemental oxygen.
If 50% of patients with COPD used myCOPD or an equivalent app, reduced admission rates for acute exacerbations would equate to a minimum approximate annual saving of
84,000
bed days
150
nurses' time back for clinical care


DESKILLING
"PATIENT" → BELANGRIJKE PARTNER
CO DESIGN / SHARED DECISION MAKING
THE GIFT of TIME
KNOW YOURSELF
"COMPELLING"
"EDUCATIE NOOD" → DIGITAL SKILL
KENNIS in GEBRUIK ??
PUBLIEK
INDUSTRIE → ROL
↑ QUALITY OUTCOME
WIDE vs SMALL AI
MAN vs HORSE
DIGITAL MEDICINE
OPT-IN
ROBOTICA
HYPE vs REALITY
BIAS EQUITY
WIE BEGRIJPT / DEFINIEERT AI
OPERATIONELE DEFINITIE
'WAARHEID' is niet langer meer
de standaard der dingen.
CAUSAAL ??
verantwoordelijkheid
mogelijkheid
wie beslist ??
WIE?
Humane aspect → patiënt bijdrage
NO PROOF
Moreel kompas
Schaal
bias
pure accuracy vs betrouwbaarheid
wiens belangen → maatschappelijke

Kelly et al. BMC Medicine (2019) 17:195
https://doi.org/10.1186/s12916-019-1426-2

BMC Medicine

OPINION Open Access

Key challenges for delivering clinical impact with artificial intelligence

Christopher J. Kelly[1*], Alan Karthikesalingam[1], Mustafa Suleyman[2], Greg Corrado[3] and Dominic King[1]

Abstract

Background: Artificial intelligence (AI) research in healthcare is accelerating rapidly, with potential applications being demonstrated across various domains of medicine. However, there are currently limited examples of such techniques being successfully deployed into clinical practice. This article explores the main challenges and limitations of AI in healthcare, and considers the steps required to translate these potentially transformative technologies from research to clinical practice.

Main body: Key challenges for the translation of AI systems in healthcare include those intrinsic to the science of machine learning, logistical difficulties in implementation, and consideration of the barriers to adoption as well as of the necessary sociocultural or pathway changes. Robust peer-reviewed clinical evaluation as part of randomised controlled trials should be viewed as the gold standard for evidence generation, but conducting these in practice may not always be appropriate or feasible. Performance metrics should aim to capture real clinical applicability and be understandable to intended users. Regulation that balances the pace of innovation with the potential for harm, alongside thoughtful post-market surveillance, is required to ensure that patients are not exposed to dangerous interventions nor deprived of access to beneficial innovations. Mechanisms to enable direct comparisons of AI systems must be developed, including the use of independent, local and representative test sets. Developers of AI algorithms must be vigilant to potential dangers, including dataset shift, accidental fitting of confounders, unintended discriminatory bias, the challenges of generalisation to new populations, and the unintended negative consequences of new algorithms on health outcomes.

Conclusion: The safe and timely translation of AI research into clinically validated and appropriately regulated systems that can benefit everyone is challenging. Robust clinical evaluation, using metrics that are intuitive to clinicians and ideally go beyond measures of technical accuracy to include quality of care and patient outcomes, is essential. Further work is required (1) to identify themes of algorithmic bias and unfairness while developing mitigations to address these, (2) to reduce brittleness and improve generalisability, and (3) to develop methods for improved interpretability of machine learning predictions. If these goals can be achieved, the benefits for patients are likely to be transformational.

Keywords: Artificial intelligence, Machine learning, Algorithms, Translation, Evaluation, Regulation

The Parable of Google Flu: Traps in Big Data Analysis

David Lazer,[1,2*] Ryan Kennedy,[1,3,4] Gary King,[3] Alessandro Vespignani[5]

IBM Watson Flops For Cancer Treatment: Why Did AI Fail?

Opinion

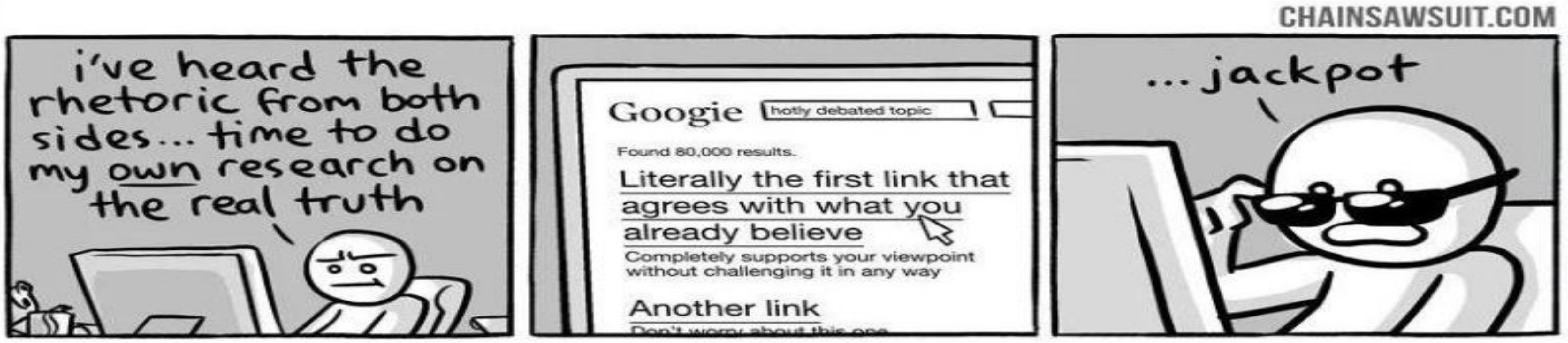
VIEWPOINT

Challenges to the Reproducibility of Machine Learning Models in Health Care

Andrew L. Beam, PhD
Department of Epidemiology, Harvard T.H. Chan School of Public Health, Boston, Massachusetts; and Department of Biomedical Informatics, Harvard Medical School, Boston, Massachusetts.

Reproducibility has been an important and intensely debated topic in science and medicine for the past few decades.[1] As the scientific enterprise has grown in scope and complexity, concerns regarding how well new findings can be reproduced and validated across different scientific teams and study populations have emerged. In some instances,[2] the failure to replicate numerous previous studies has added to the growing concern that science and biomedicine may be in the midst of a "repro- ways the case for machine learning studies) because these data are often biased, and models could operationalize this bias if not replicated. The challenges of reproducing a machine learning model trained by another research team can be difficult, perhaps even prohibitively so, even with unfettered access to raw data and code.

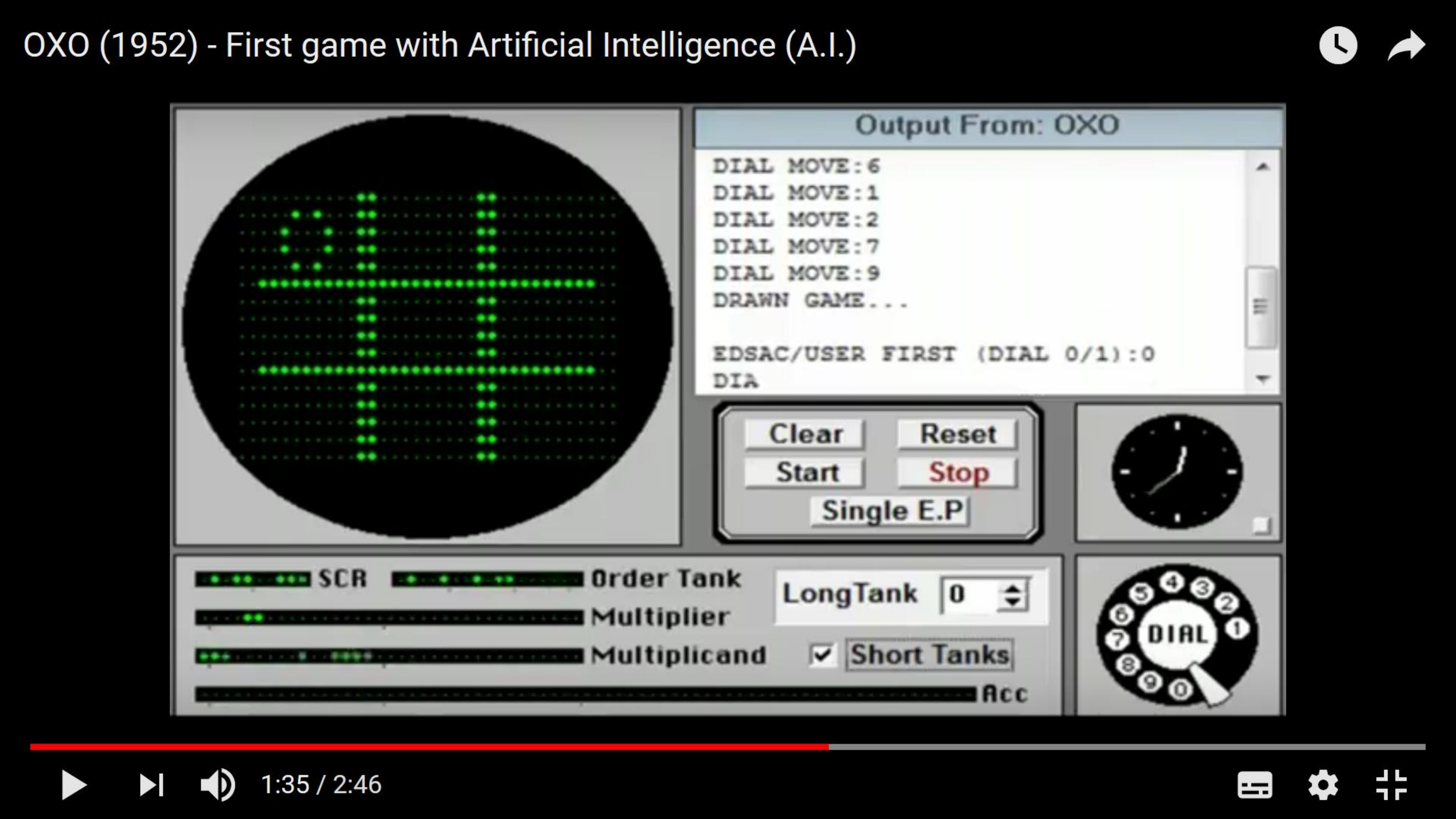
Unique Challenges to Reproducibility Posed by Machine Learning

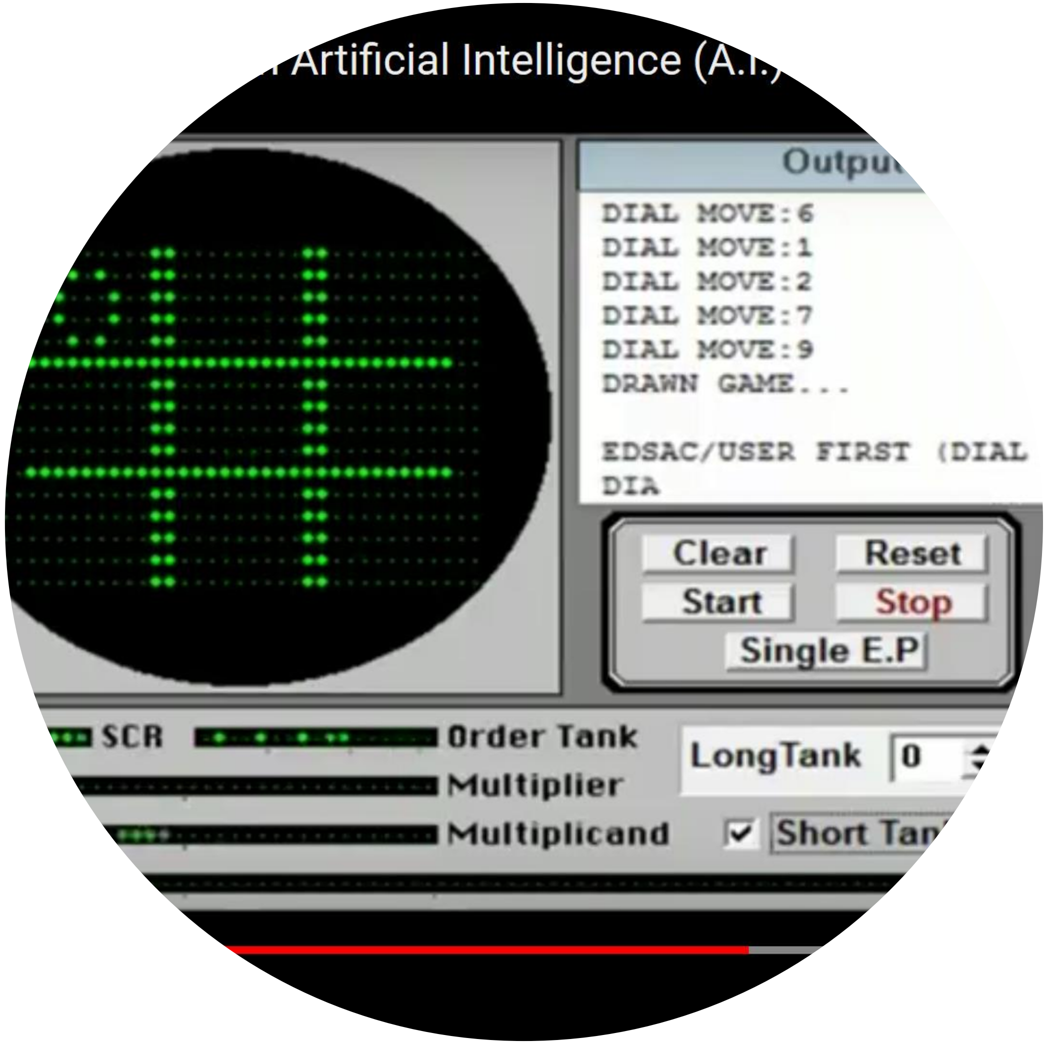


Intrinsic problems/opportunities of AI
Intrinsic problems/opportunities of Big data
Intrinsic problems /opportunities of health care

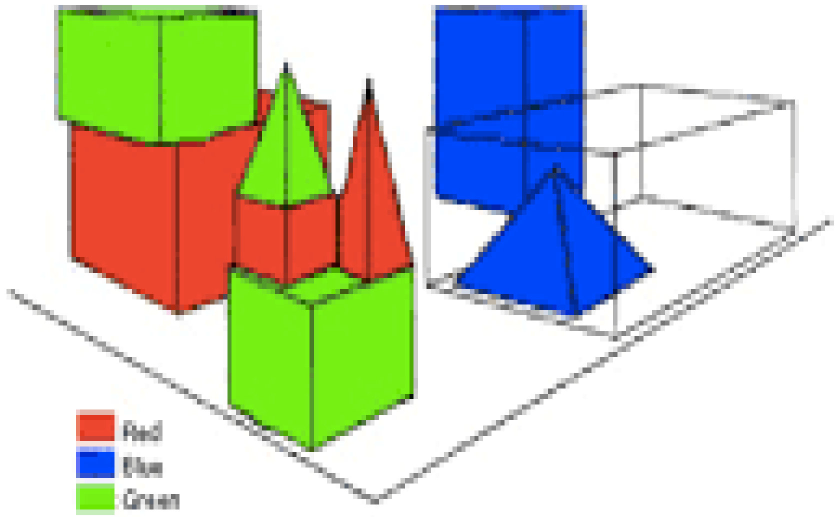
Artificial Intelligence (AI)

That what makes a machine behave in a way we would call intelligent if it was done by a human


OXO (1952) - First game with Artificial Intelligence (A.I.)
Output From: OXO
DIAL MOVE:6
DIAL MOVE:1
DIAL MOVE:2
DIAL MOVE:7
DIAL MOVE:9
DRAWN GAME...
EDSAC/USER FIRST (DIAL 0/1):0
DIA
Clear
Reset
Start
Stop
Single E.P
SCR
Order Tank
Multiplier
Multiplicand
Acc
LongTank
0
Short Tanks
DIAL
1:35 / 2:46



Artificial Intelligence (A.I.)
Outpu
DIAL MOVE:6
DIAL MOVE:1
DIAL MOVE:2
DIAL MOVE:7
DIAL MOVE:9
DRAWN GAME...
EDSAC/USER FIRST (DIAL
DIA
Clear
Reset
Start
Stop
Single E.P
SCR
Order Tank
Multiplier
Multiplicand
LongTank
0
Short Tan



Person: Pick up a big red block.

Computer: OK.

Person: Grasp the pyramid.

Computer: I don't understand which pyramid you mean.

SHRDLU language

Conceptualisation of the world

Manipulating symbols:
2+2=4; 4+2=6; 2+2+2=6
***\$*£%; %\$*£M; *\$*\$*\$£M**

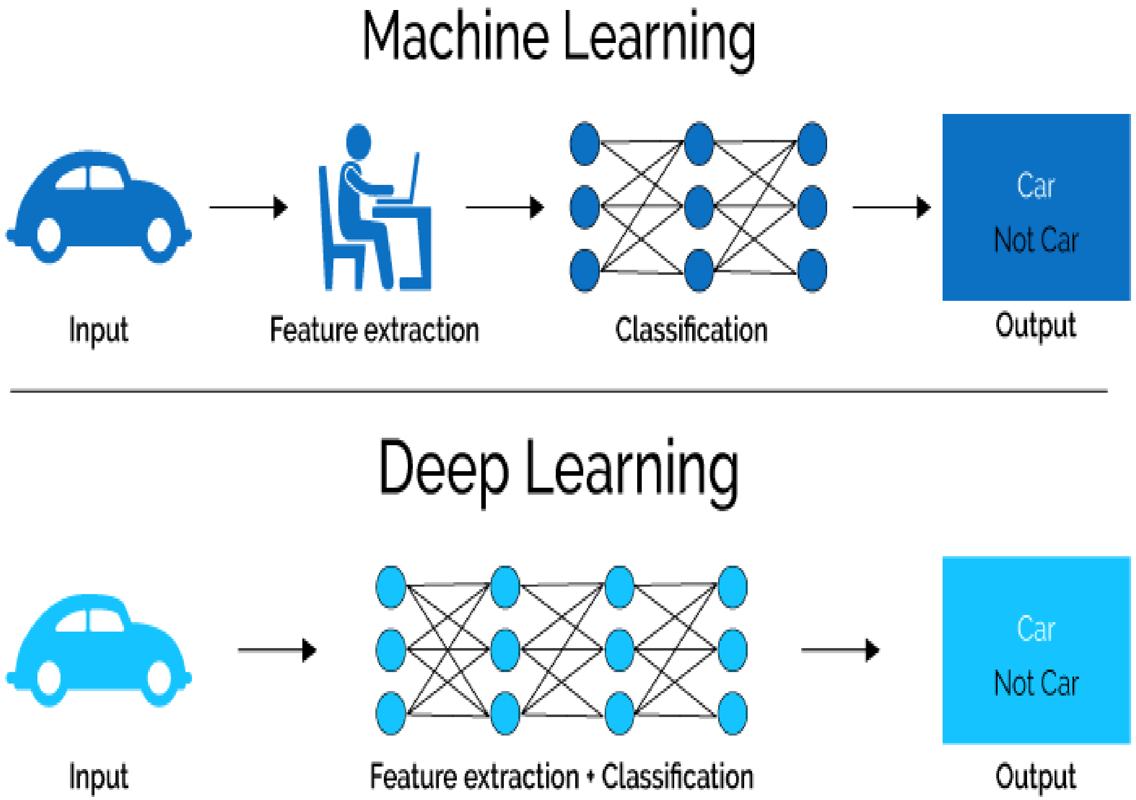
Creating "meaning"

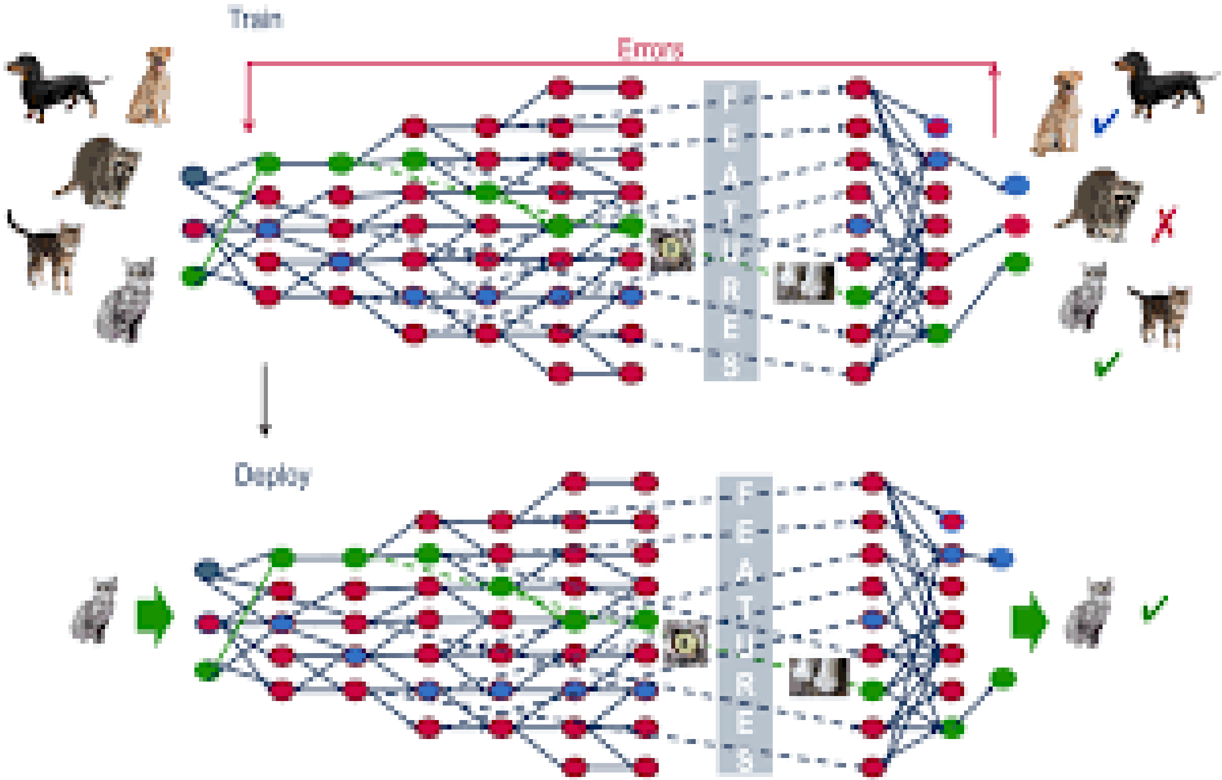
SHRDLU language

Conceptualisation of the world

Manipulating symbols:
2+2=4; 4+2=6;
2+2+2=6
***$*£%; %$*£M;**
***$*$*$£M**

~~Creating "meaning"~~


Machine Learning
Input
Feature extraction
Classification
Car
Not Car
Output
Deep Learning
Input
Feature extraction + Classification
Car
Not Car
Output


Train
Errors
FEATURES
Deploy
FEATURES

Deep Learning

- Pattern recognition-Classification // Prediction
- Only recognizes what it has seen before; will always guess an answer
- Black box: very hard to find out HOW or WHY the answer is what the answer is

RESEARCH ARTICLE

Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study

John R. Zech[1☯], Marcus A. Badgeley[2☯], Manway Liu[2], Anthony B. Costa[3], Joseph J. Titano[4], Eric Karl Oermann[3*]

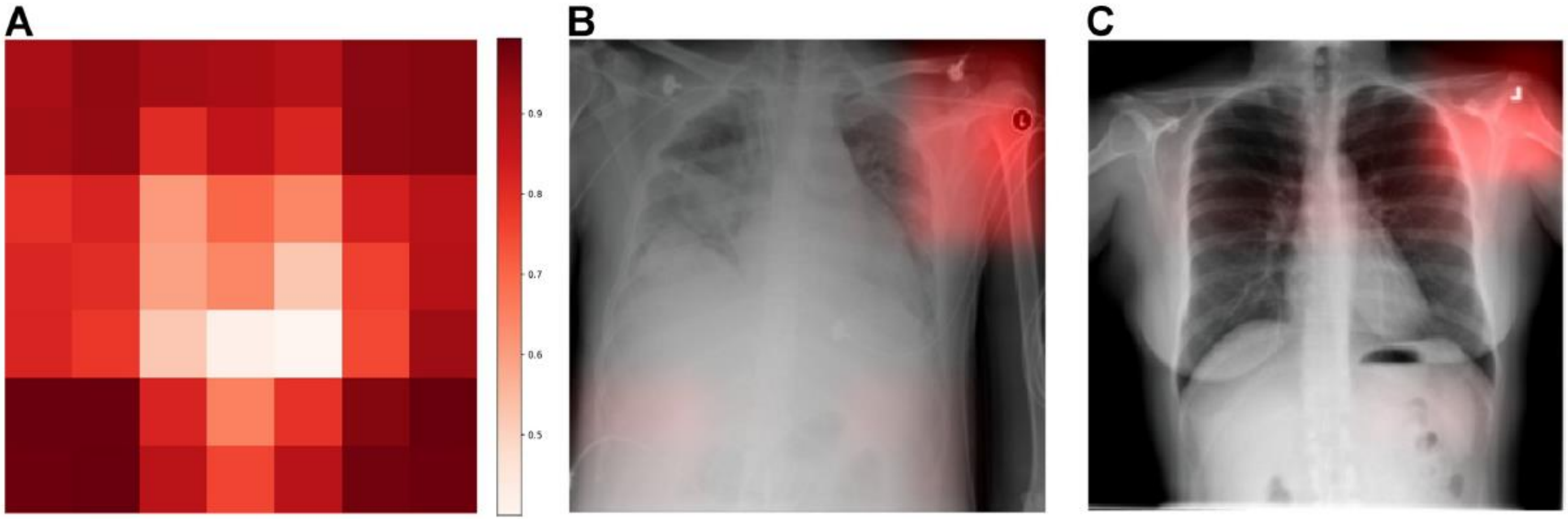
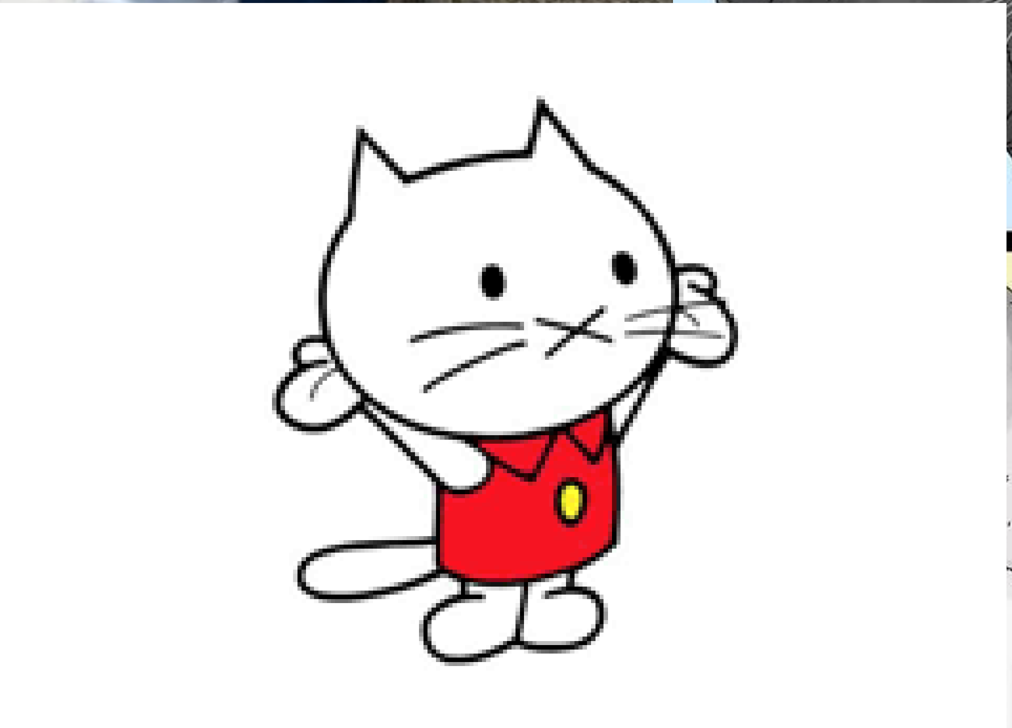


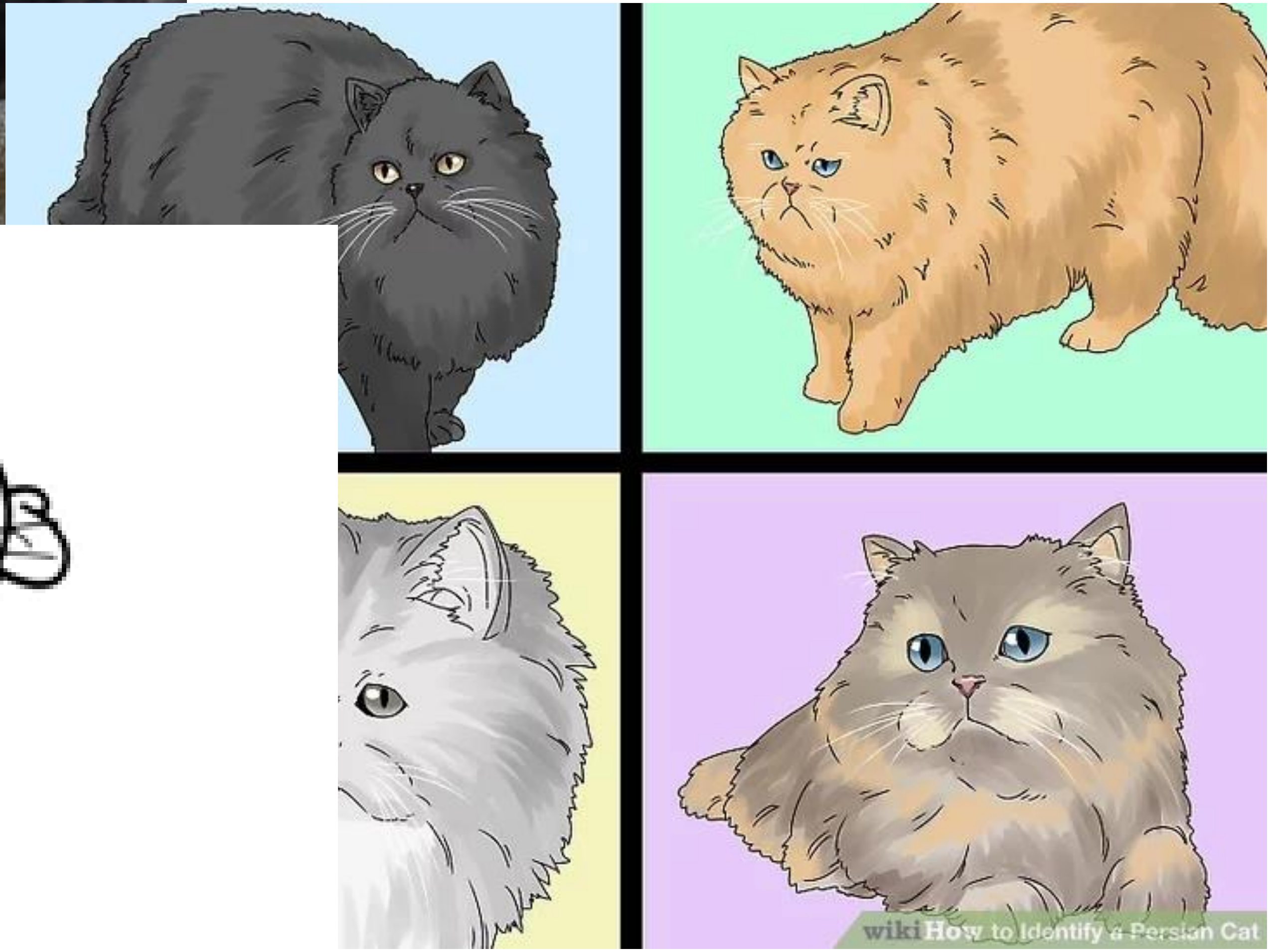
Fig 2. CNN to predict hospital system detects both general and specific image features. (A) We obtained activation heatmaps from our trained model and averaged over a sample of images to reveal which subregions tended to contribute to a hospital system classification decision. Many different subregions strongly predicted the correct hospital system, with especially strong contributions from image corners. (B-C) On individual images, which have been normalized to highlight only the most influential regions and not all those that contributed to a positive classification, we note that the CNN has learned to detect a metal token that radiology technicians place on the patient in the corner of the image field of view at the time they capture the image. When these strong features are correlated with disease prevalence, models can leverage them to indirectly predict disease. CNN, convolutional neural network.

Deep Learning

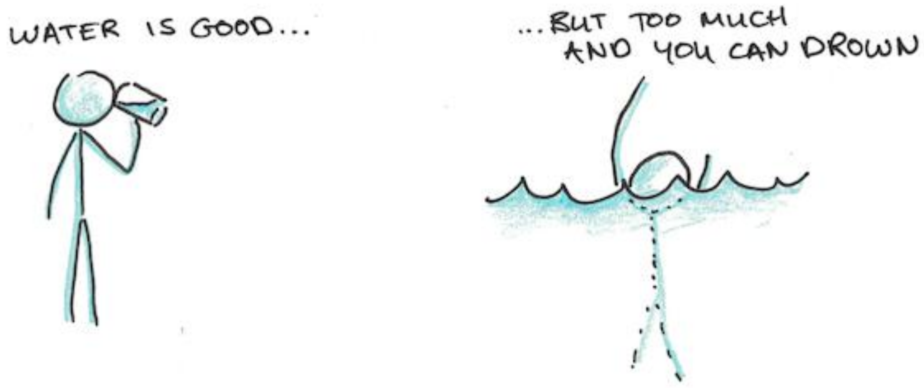
- Pattern recognition
- Only recognizes what it has seen before; will always guess an answer
- Black box: very hard to find out HOW or WHY the answer is what the answer is
- Need for (big) trainingsets (Big data)


wikiHow to Identify a Persian Cat




wikiHow to Identify a Persian Cat

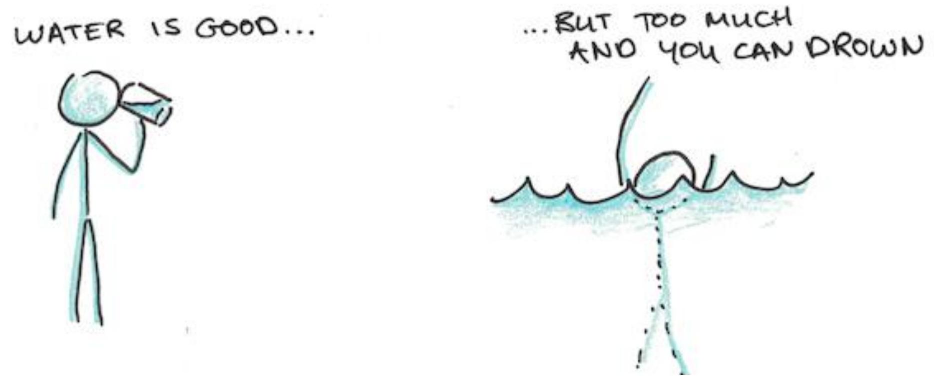
Time (and thus potential causality)



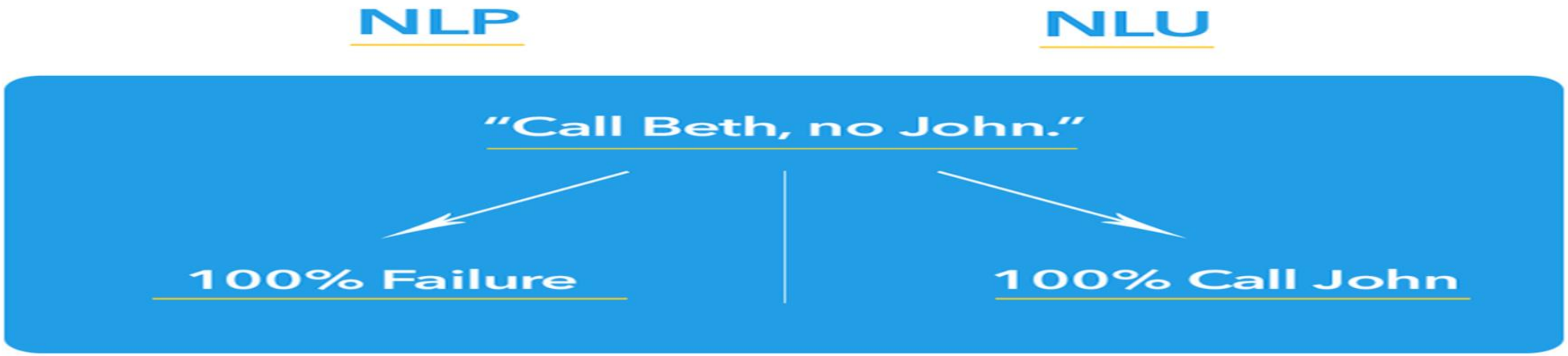
context

Did Napoleon have an Apple or an Android smartphone?

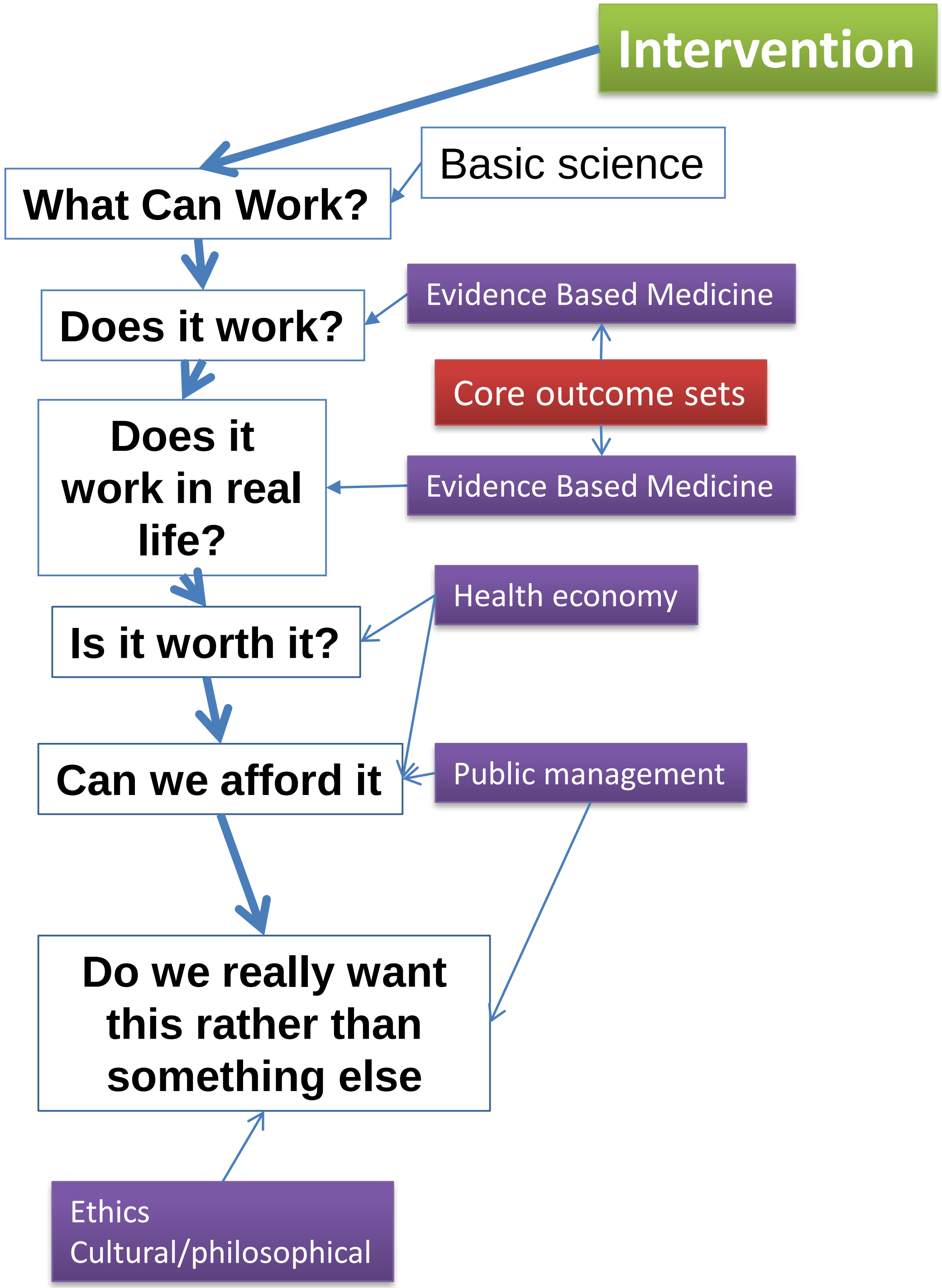
Did Napoleon have an Apple or an Android smartphone?



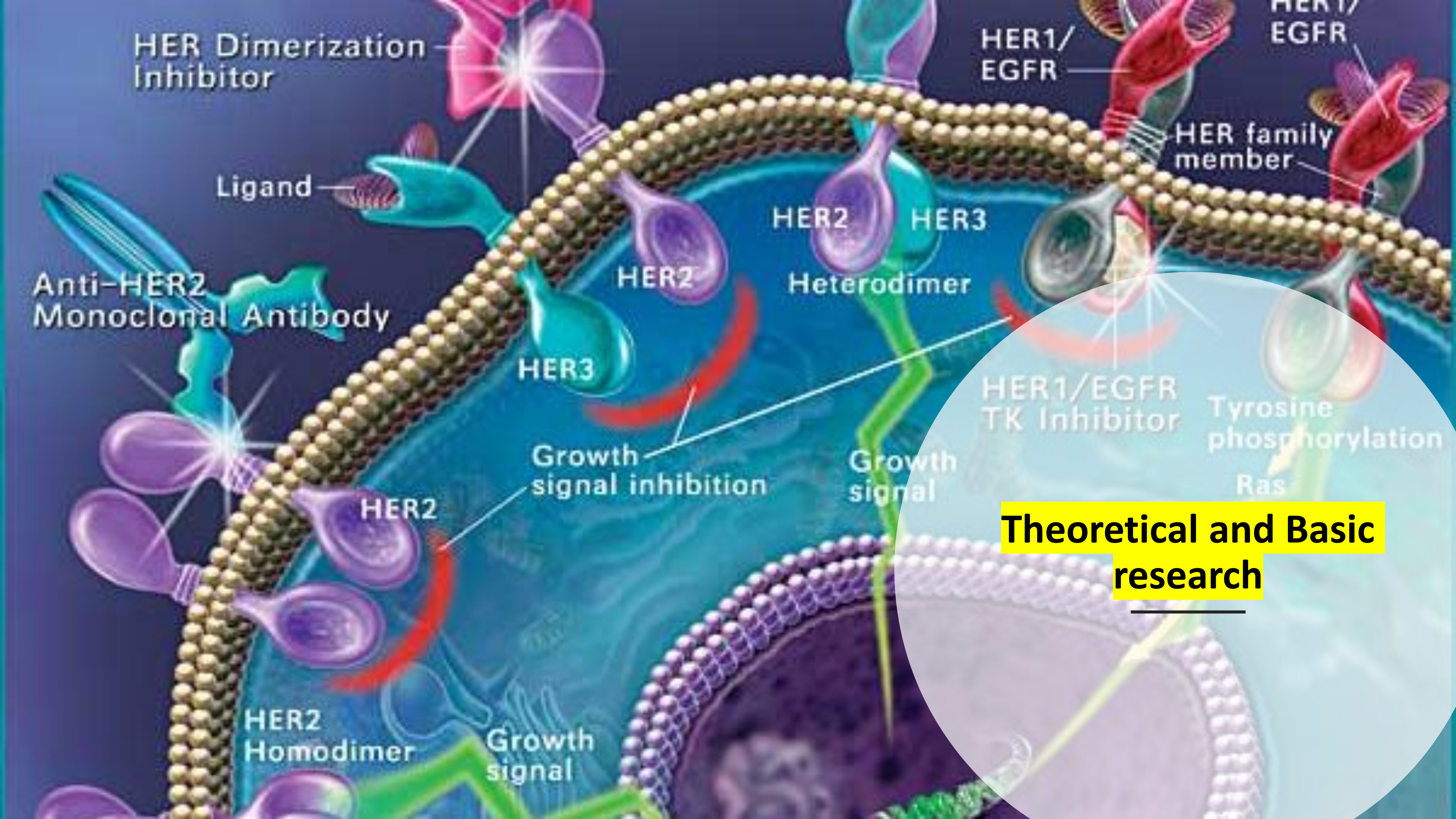
context



meaning


Intervention
What Can Work?
Basic science
Does it work?
Evidence Based Medicine
Core outcome sets
Does it work in real life?
Evidence Based Medicine
Is it worth it?
Health economy
Can we afford it
Public management
Do we really want this rather than something else
Ethics
Cultural/philosophical

Theoretical and Basic research



Intervention

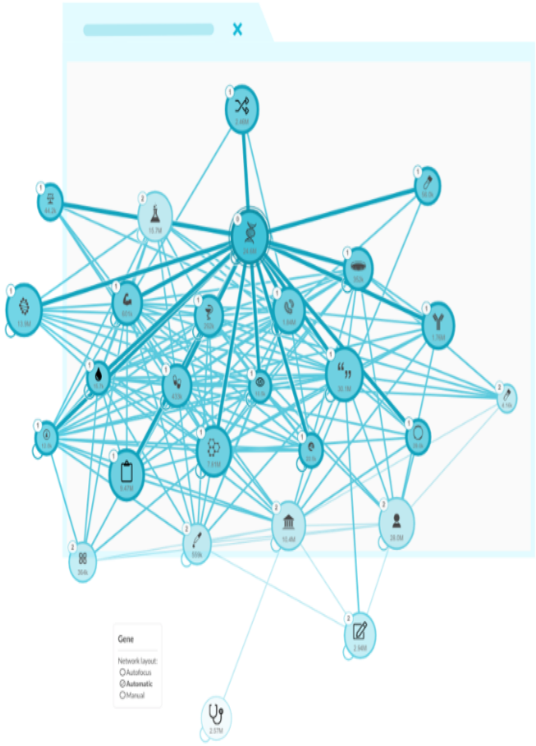
Basic science

Can it work?

ONTOFORCE

SOLUTIONS PLATFORM COMMUNITY ABOUT CONTACT

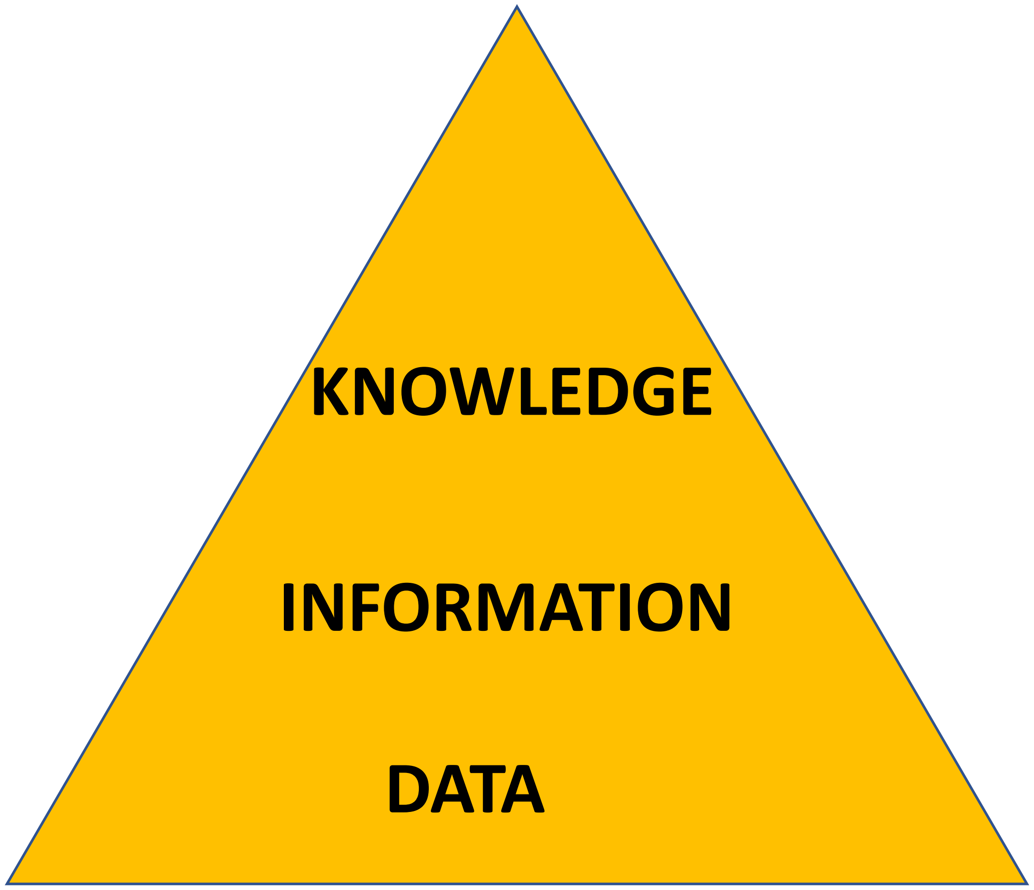
GO TO DISQOVER PUBLIC



Build a Scalable Enterprise Linked Data Fabric

Enjoy the benefits of FAIR data, facilitating interoperability and connectivity with other applications. The DISQOVER open plug-in architecture allows you to seamlessly connect specialized artificial intelligence (AI) services to annotated, standardized and structured data.

READ MORE


KNOWLEDGE
INFORMATION
DATA

Intervention

Can it work?

Basic science

Does it work?

Evidence Based Medicine

Decision making on (medical) actions, intentionally based on a TRANSPARANT and SYSTEMATIC analysis of available evidence, and this applied to a REAL LIFE clinical context

Evidence Based Medicine

Decision making on (medical) actions, intentionally based on a transparant and systematic analysis of available evidence, and this applied to a real-life clinical context

With the goal to decrease the
DISCREPANCY
between
medical actions
And
Medical knowledge

Evidence Based Medicine
Randomized Controlled Trial

Randomisation to ensure that the only difference between two experimental groups is the intervention under scrutiny

Causality

Automated, electronic alerts for acute kidney injury: a single-blind, parallel-group, randomised controlled trial

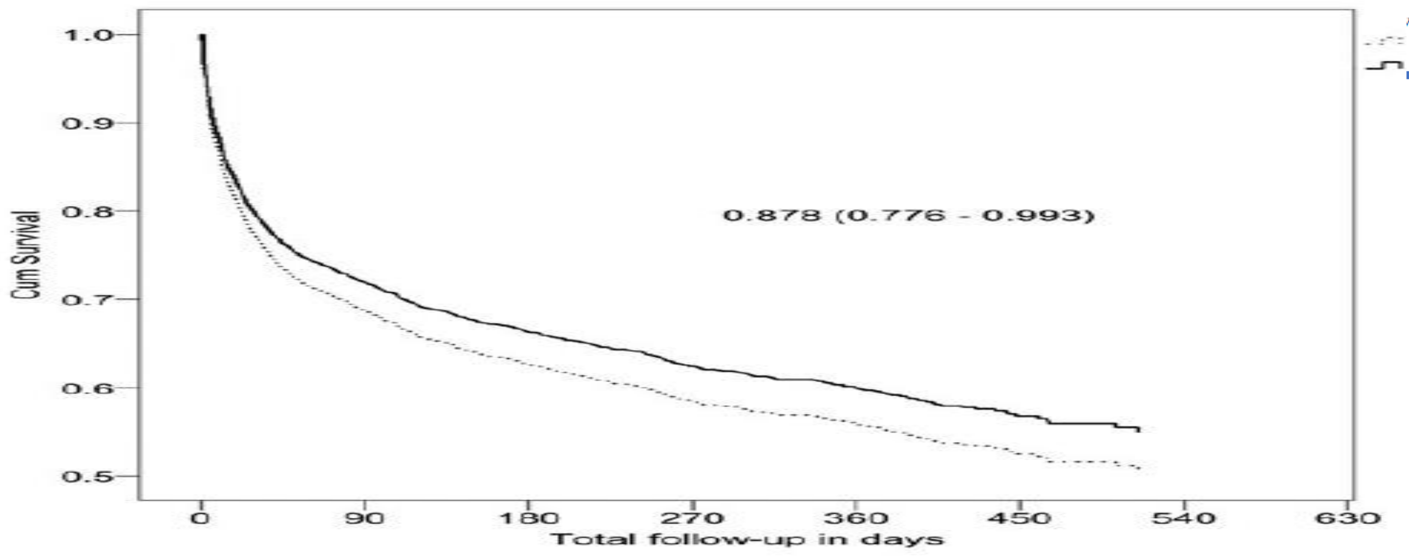
F Perry Wilson, Michael Shashaty, Jeffrey Testani, Iram Aqeel, Yuliya Borovskiy, Susan S Ellenberg, Harold I Feldman, Hilda Fernandez, Yevgeniy Gitelman, Jennie Lin, Dan Negoianu, Chirag R Parikh, Peter P Reese, Richard Urbani, Barry Fuchs

Nephrol Dial Transplant (2016) 0: 1–9
doi: 10.1093/ndt/gfw087

ndt
Nephrology Dialysis Transplantation

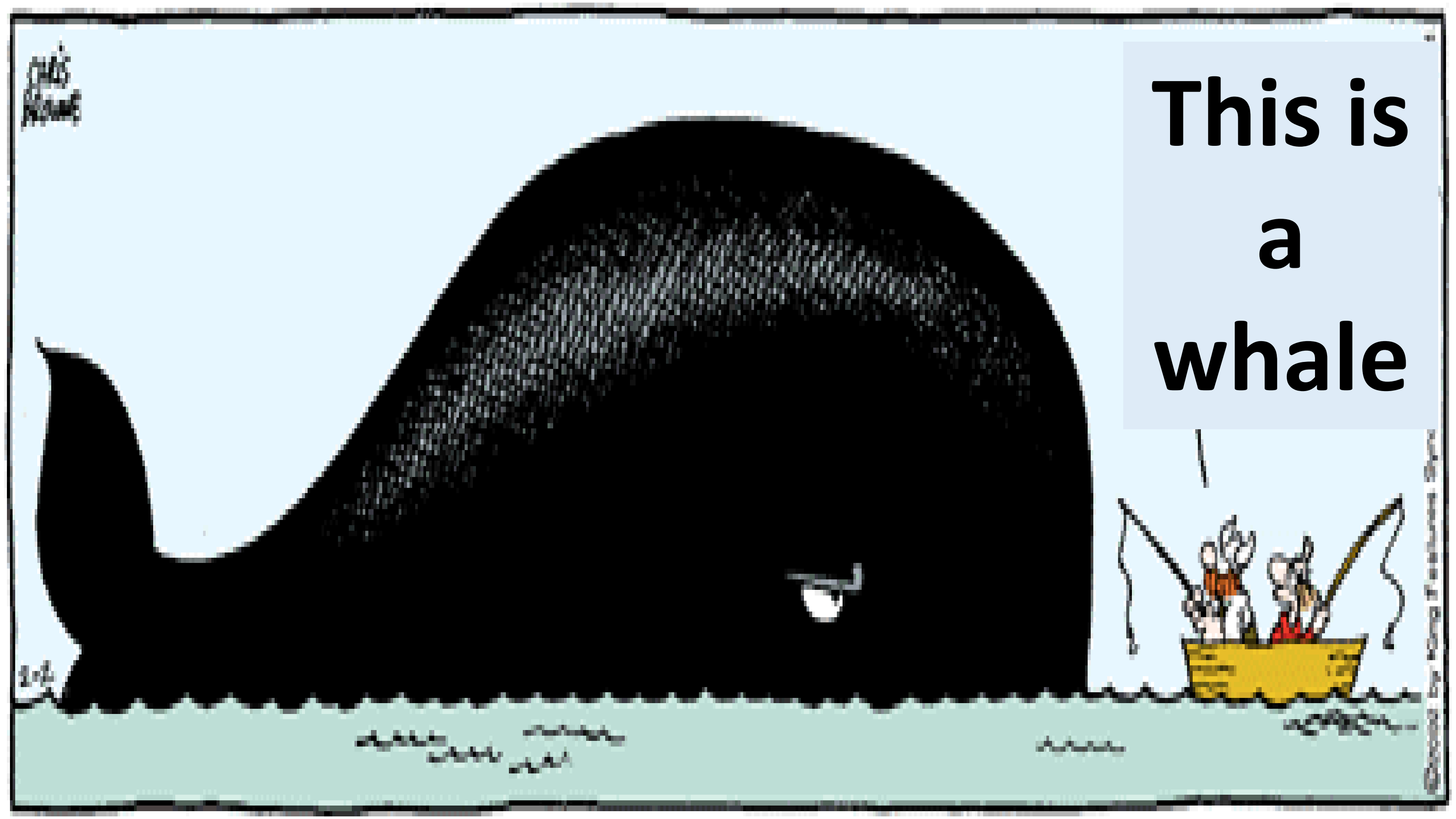
Original Article

A simple care bundle for use in acute kidney injury: a propensity score matched cohort study



No at risk							
AKI-CB complete	939	910	860	800	765	670	573
AKI-CB not completed	1823	1752	1614	1483	1342	1197	1035

Evidence Based Medicine
Randomized Controlled Trial



Systematic review

Data mining: systematic reviews

Deep learning/artificial intelligence/big data could help to

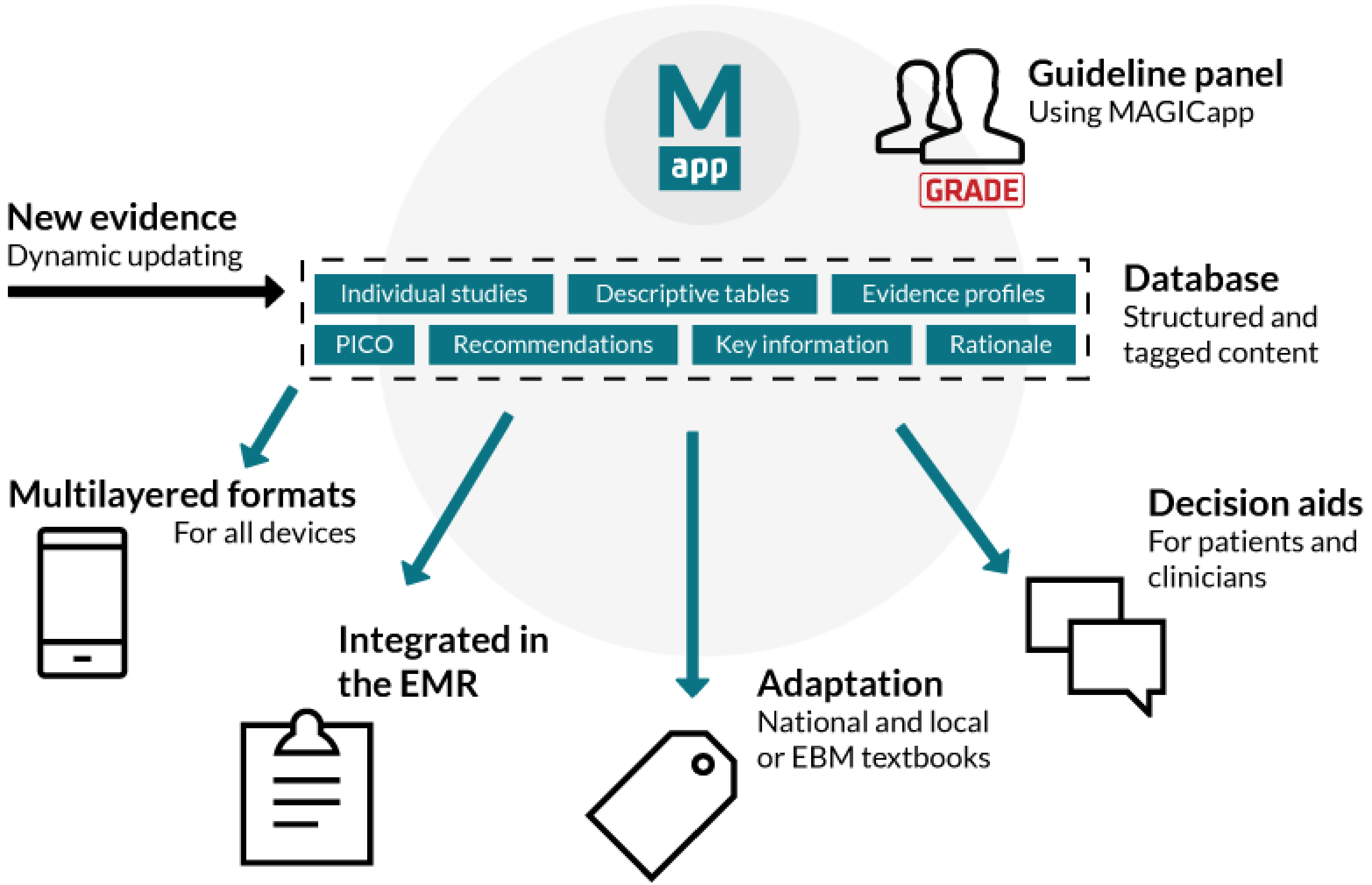
- **identify and select relevant literature/data**
- **extraction of relevant data**
- **presentation of data**

Data mining: systematic reviews

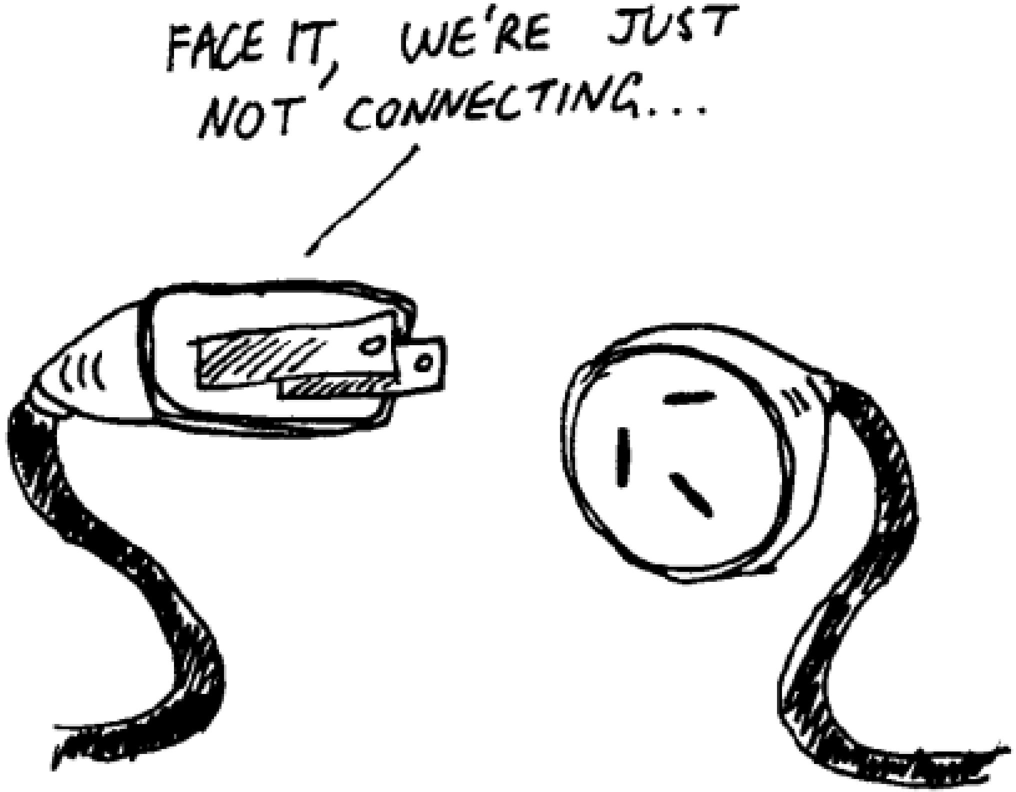
Chapter 1.1. Continued

Author	Publication Year	N HD	N PD	Outcome	Observation time	Effect Measure	Value Effect Measure	Lower Bound Confidence Interval	Upper Bound Confidence Interval
Collins [226]	2004	26049	2805	Death rates per 1000 patient years	30–36 months	Relative risk	1.79	2.22	1.41
Couchoud [230]	2007	991	191	Death in patients aged 75 years and over	0–2 years	Hazard ratio	1.00	0.80	1.30
Ganesh [227]	2003	28392	4651	Death in patients without CAD	12–18 months	Relative risk	1.57	1.34	1.85
Ganesh [227]	2003	12905	1844	Death in patients with CAD	12–18 months	Relative risk	1.35	1.17	1.54
Ganesh [227]	2003	12905	1844	Death in patients with CAD	0–2 years	Relative risk	1.23	1.12	1.34
Ganesh [227]	2003	28392	4651	Death in diabetic patients without CAD	0–2 years	Relative risk	1.17	1.08	1.26
Ganesh [227]	2003	28392	4651	Death in patients without CAD	18–24 months	Relative risk	1.39	1.11	1.75
Ganesh [227]	2003	12905	1844	Death in patients with CAD	18–24 months	Relative risk	1.31	1.09	1.57
Lee [231]	2009	437	79	Death in diabetic patients	0–2 years	Hazard ratio	0.93	0.41	2.12
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic men aged 20–44 years	0–3 years	Hazard ratio	0.86	0.45	1.68
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic men aged 45–59 years	0–3 years	Hazard ratio	0.79	0.54	1.15
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic men aged 60–69 years	0–3 years	Hazard ratio	0.96	0.69	1.34
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic women aged 45–59 years	0–3 years	Hazard ratio	0.80	0.47	1.38
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic men aged ≥70 years	0–3 years	Hazard ratio	0.80	0.61	1.04
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic men	0–3 years	Hazard ratio	0.84	0.71	1.00
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic women	0–3 years	Hazard ratio	1.16	0.93	1.44
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic women aged 20–44 years	0–3 years	Hazard ratio	0.76	0.33	1.76
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic women aged 60–69 years	0–3 years	Hazard ratio	0.95	0.60	1.49
van de Luijtgaarden [232]	2011	3976	955	Death in diabetic women aged ≥70 years	0–3 years	Hazard ratio	1.55	1.15	2.08
Vonesh [233]	2004	352706	46234	Death in diabetic patients aged 18–44 years without comorbidity	0–3 years	Relative risk	0.82	0.70	0.95
Vonesh [233]	2004	352706	46234	Death in diabetic patients aged 45–64 years with comorbidity	0–3 years	Relative risk	1.22	1.15	1.30
Vonesh [233]	2004	352706	46234	Death in diabetic patients aged 18–44 years with comorbidity	0–3 years	Relative risk	0.91	0.76	1.09
Vonesh [233]	2004	352706	46234	Death in diabetic patients aged ≥65 years with comorbidity	0–3 years	Relative risk	1.25	1.18	1.32

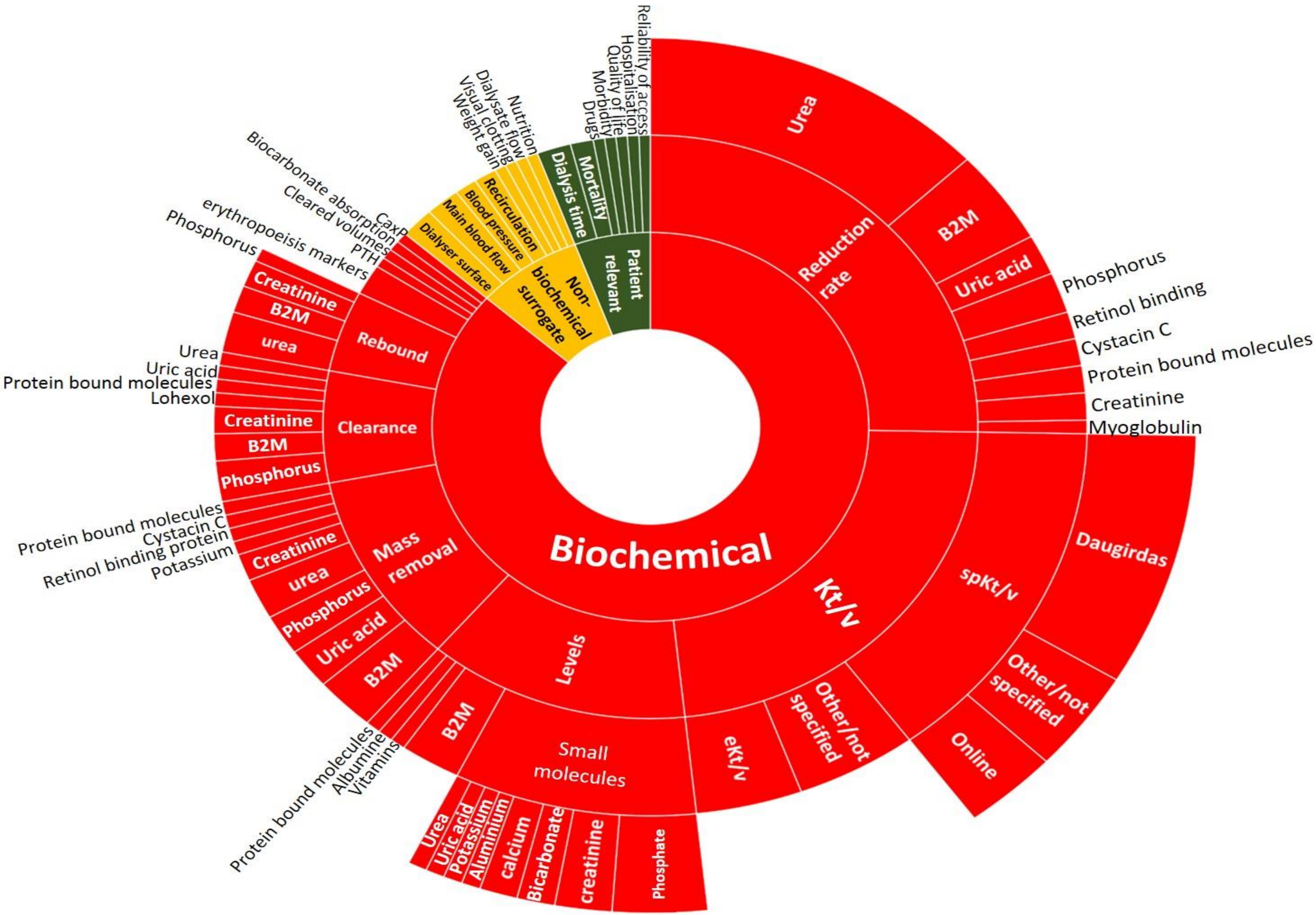
The MAGIC tool



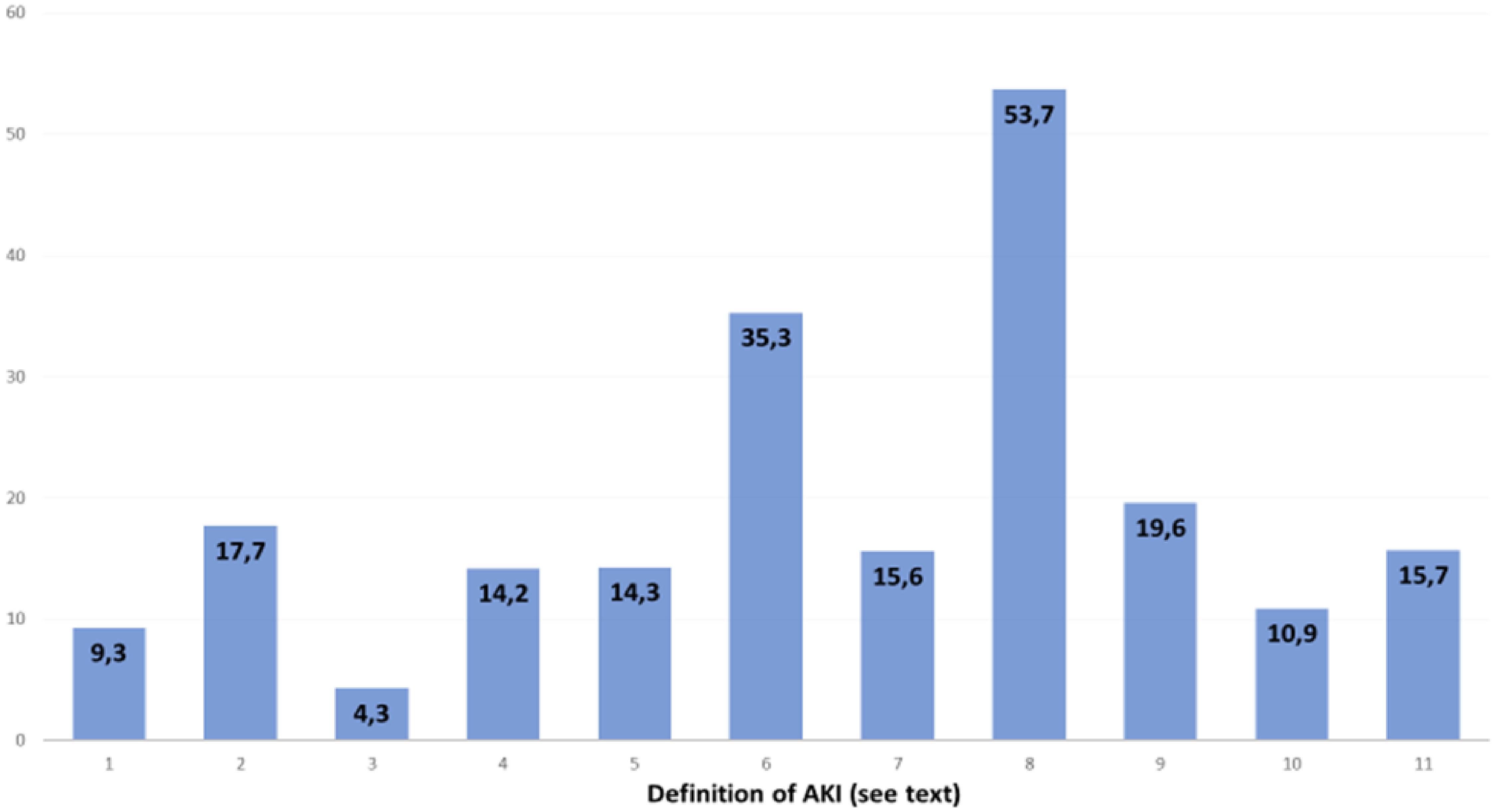
Wrong outcomes impede meta-analysis



Adequacy of dialysis: definitions in RCTs: a systematic review



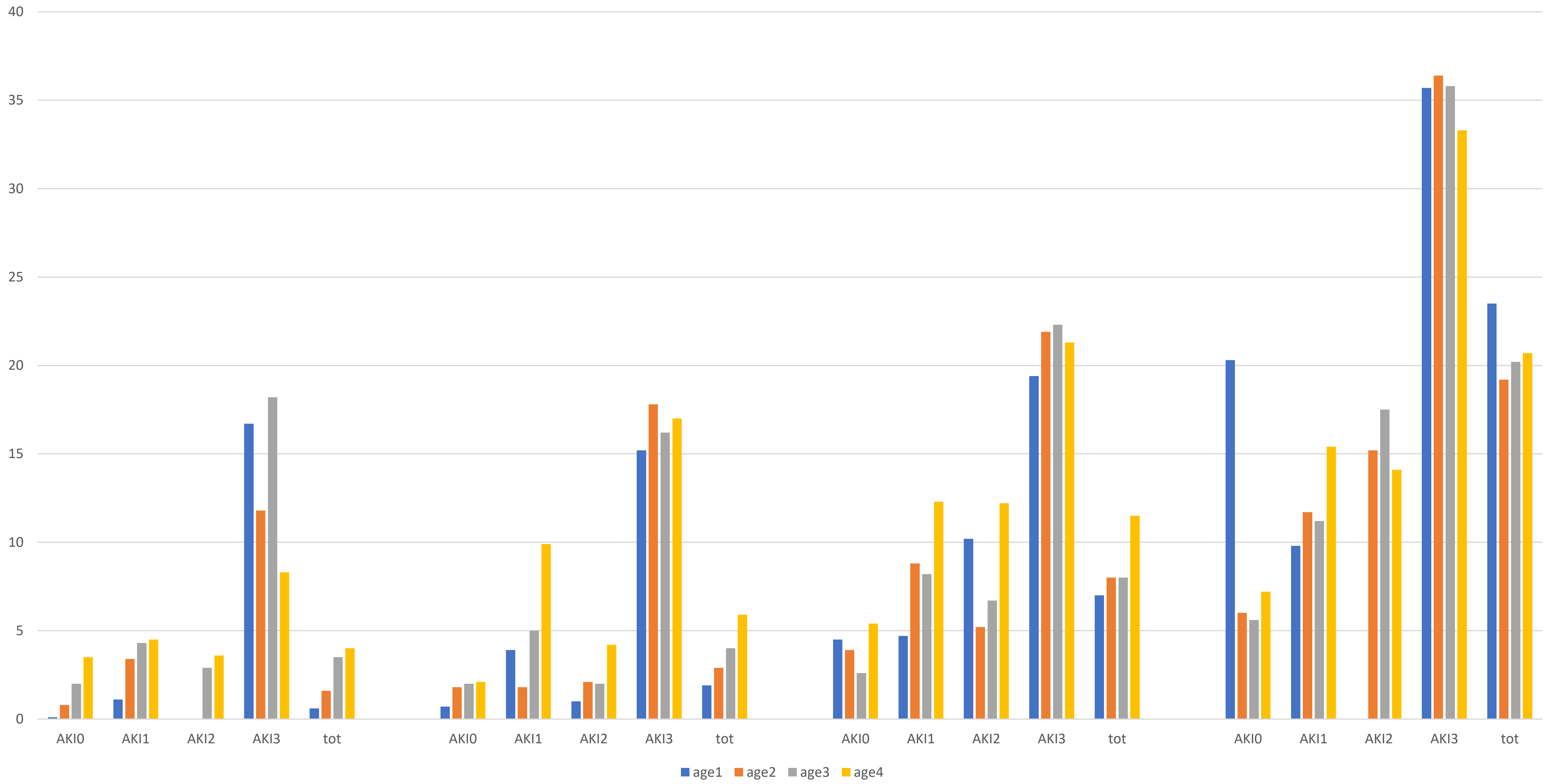
AKI: what are we talking about?



AKI: what are we talking about?

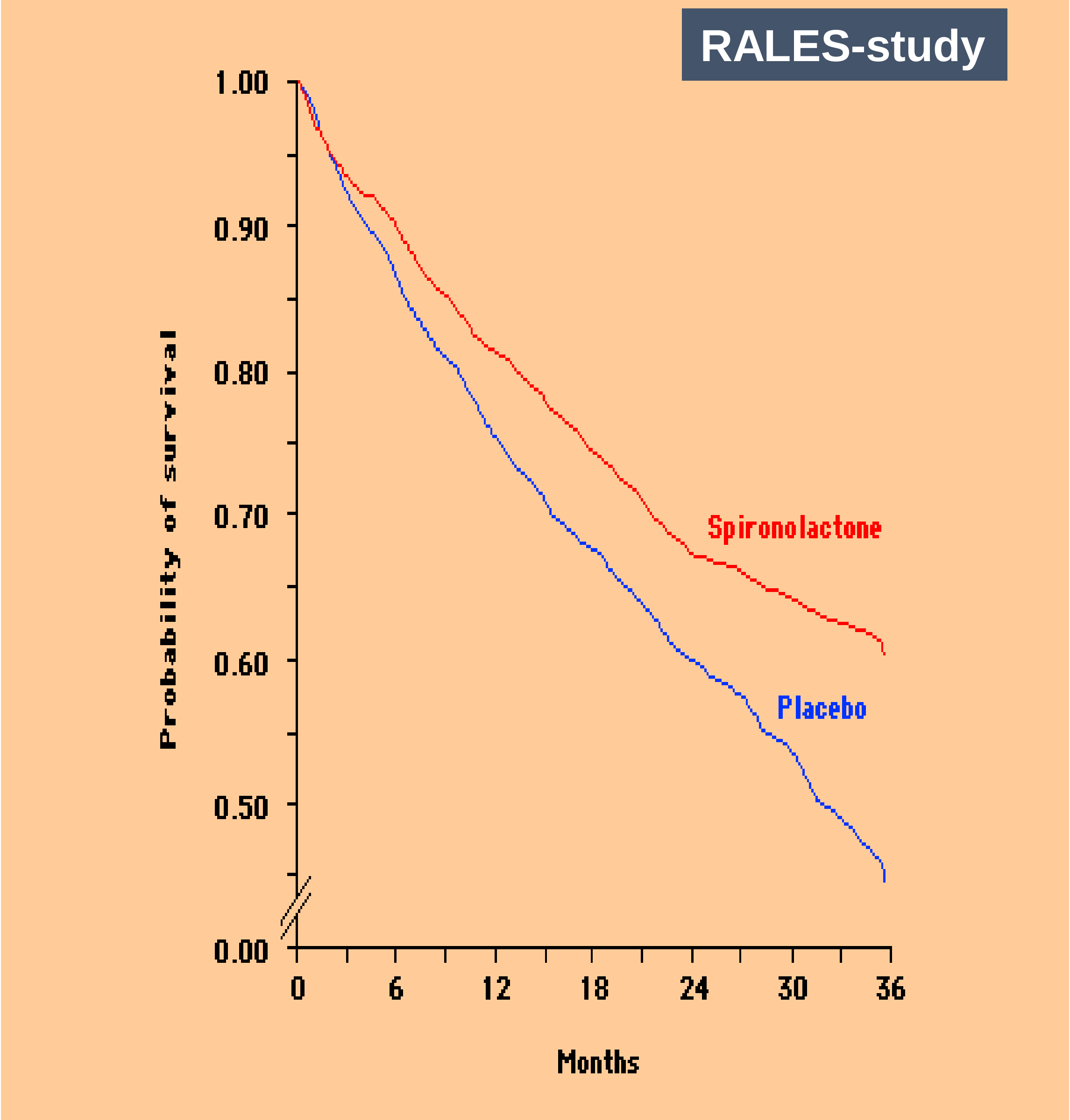
Definition (see text)	Exp Beta adjusted for age, gender and SOFA score	95% CI	Unadjusted mortality positive patients	Unadjusted mortality Negative patients
1	4.58	3.87-5.43	27.6%	5.0%
2	3.33	2.91-3.80	20.3%	5.0%
3	2.87	2.35-3.49	28.5%	6.8%
4	6.14	5.22-7.88	26.9%	4.2%
5	4.96	4.24-5.80	22.7%	4.0%
6	3.63	3.16-4.17	15.6%	4.0%
7	5.09	4.46-5.81	24.7%	5.0%
8	3.53	3.09-4.03	18.3%	4.4%
9	3.64	3.17-4.18	15.6%	4.0%
10: none of 1-9	1		3.3%	
10: only UO	2.31	1.90-2.81	7.3%	
10: only Screa	2.00	1.57-2.55	7.1%	
10: both UO and Screa	7.28	6.12-8.65	26%	

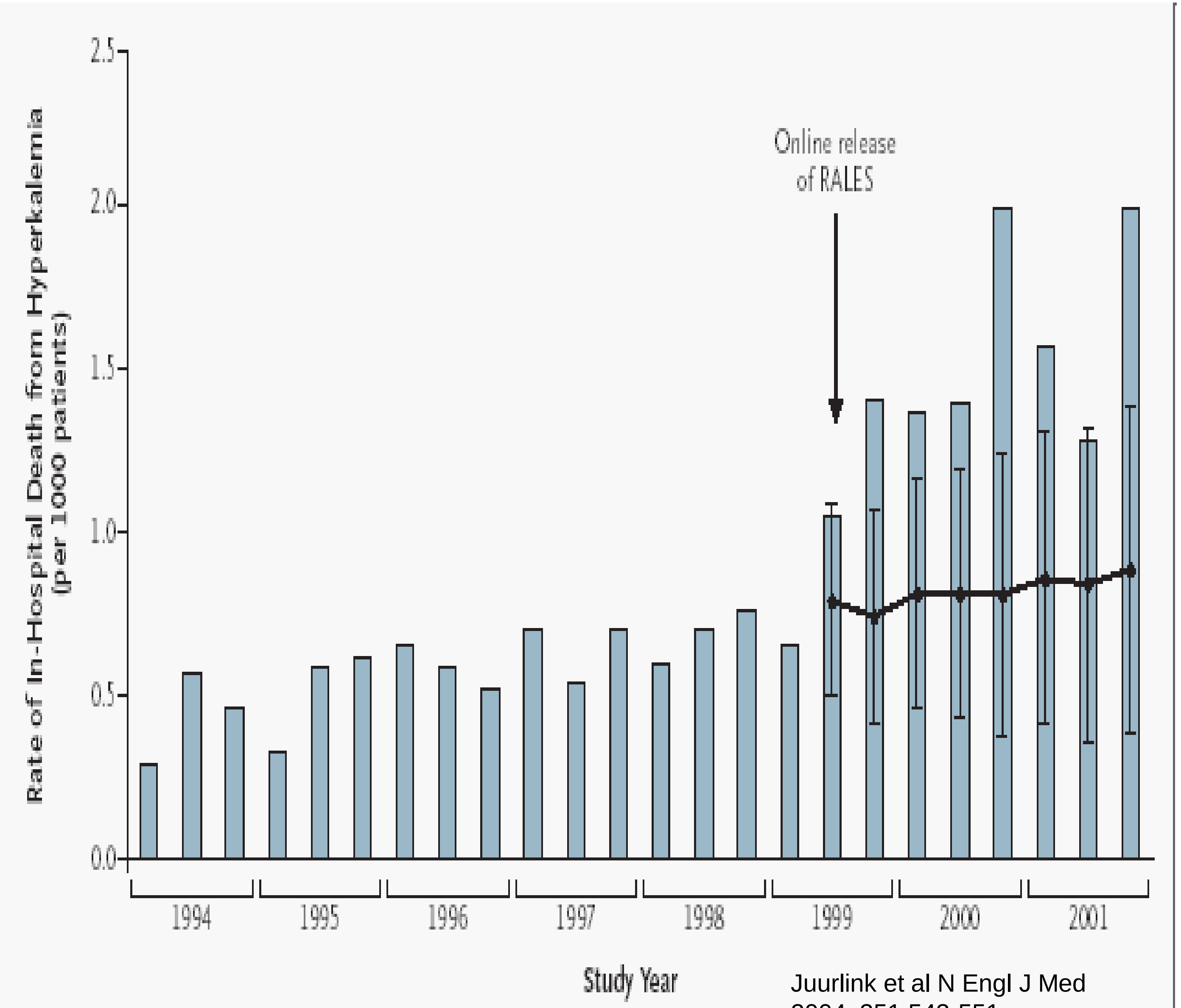
AKI: what are we talking about?



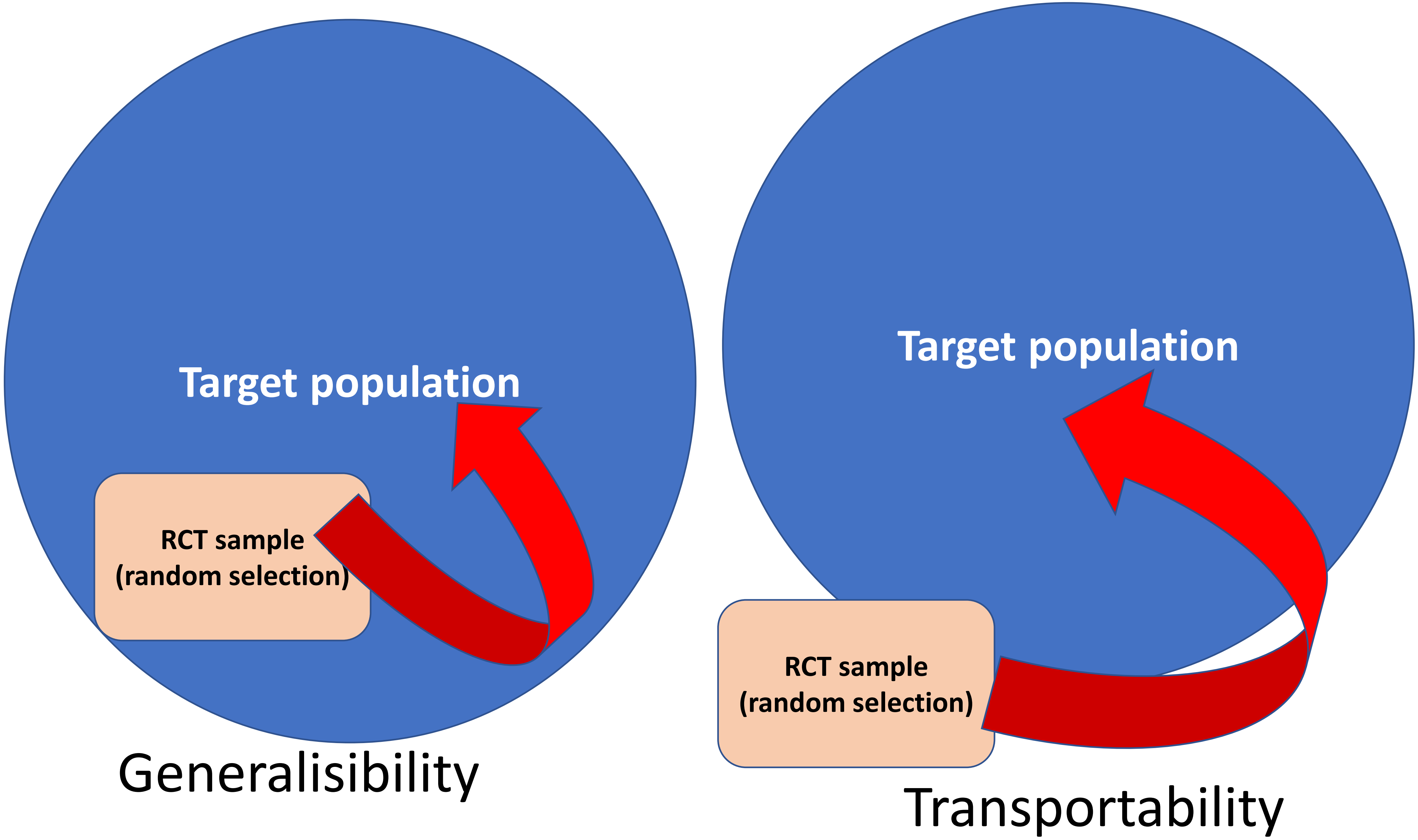
Studies vs Real Life

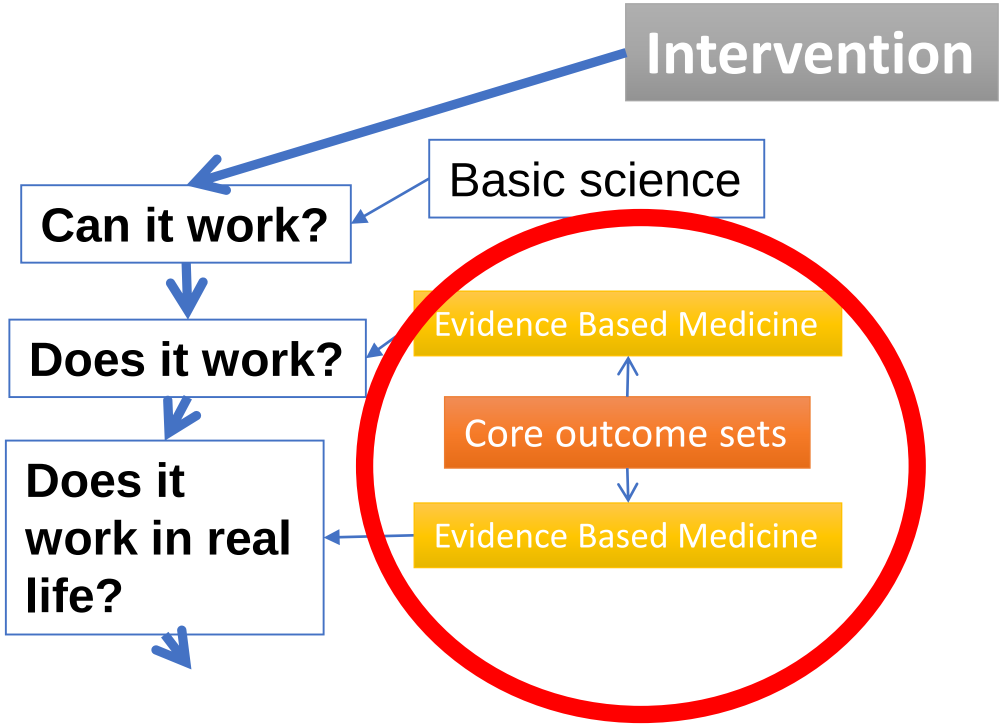
External validity





Juurlink et al N Engl J Med 2004, 351:543-551

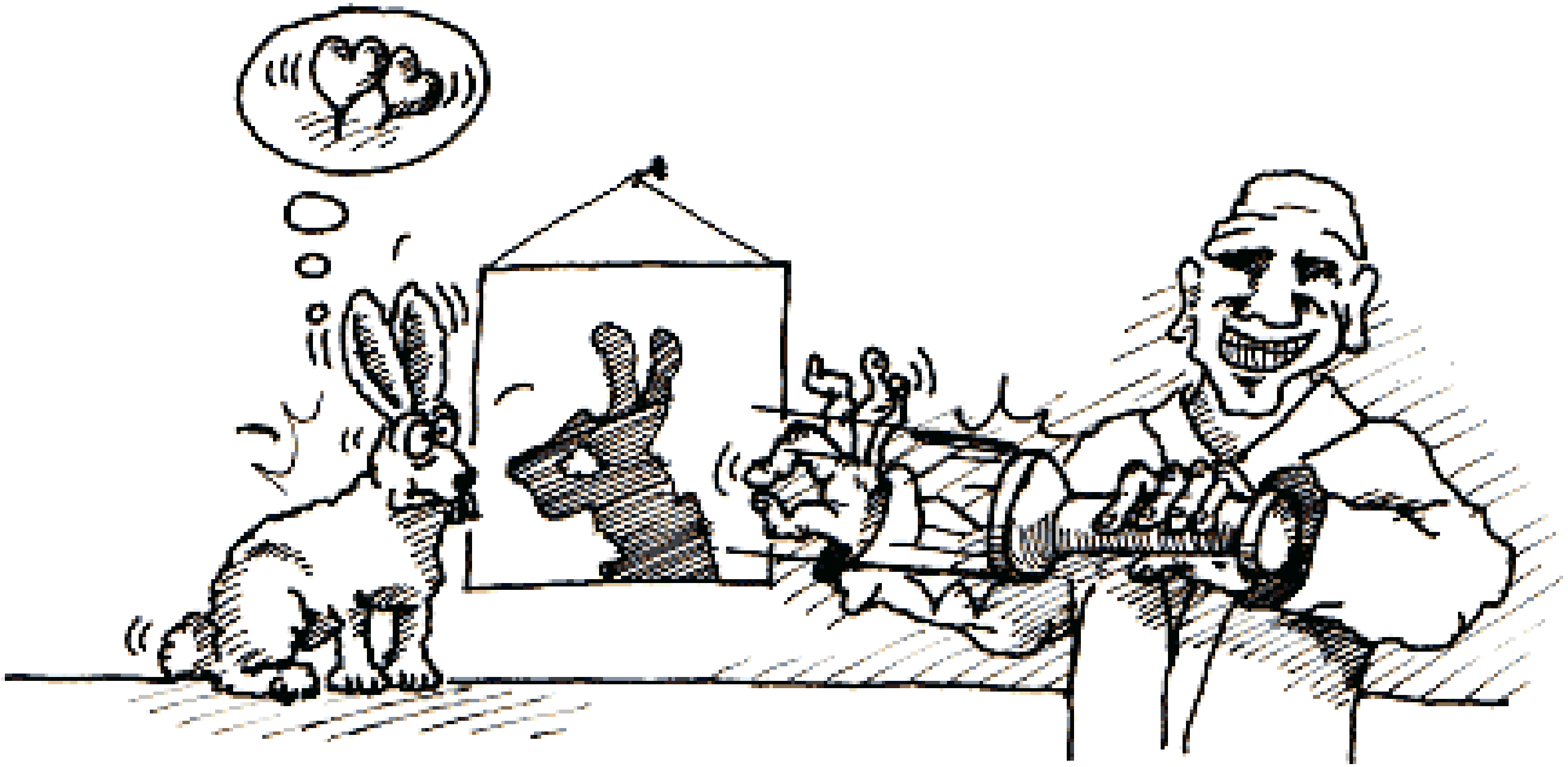

Target population
RCT sample
(random selection)
Generalisibility
Target population
RCT sample
(random selection)
Transportability



Big Data/AI can be helpful

- **Uniformisation of data**
- **Completeness of data**
- **Correctness/veracity of data**
- **Representativity of data**

Veracity
Volume
Variability
Velocity



Observational studies

NO VALUE ?

ÉTIENNE GILSON

WITH A FOREWORD BY
CHRISTOPH CARDINAL SCHÖNBORN

FROM ARISTOTLE TO DARWIN AND BACK AGAIN

A JOURNEY IN FINAL CAUSALITY, SPECIES, AND EVOLUTION

IGNATIUS

Biases in electronic health record data due to processes within the healthcare system: retrospective observational study

Denis Agniel,[1] Isaac S Kohane,[1,2] Griffin M Weber[1,3]

WHAT IS ALREADY KNOWN ON THIS TOPIC

Dynamic processes within the healthcare system, such as the hours when clinics are open and when patients are scheduled to be seen, leave an imprint on electronic health record data

WHAT THIS STUDY ADDS

An evaluation of using the effects of healthcare processes on 272 laboratory tests to predict three year survival in the full patient populations seen over a year at two large hospitals

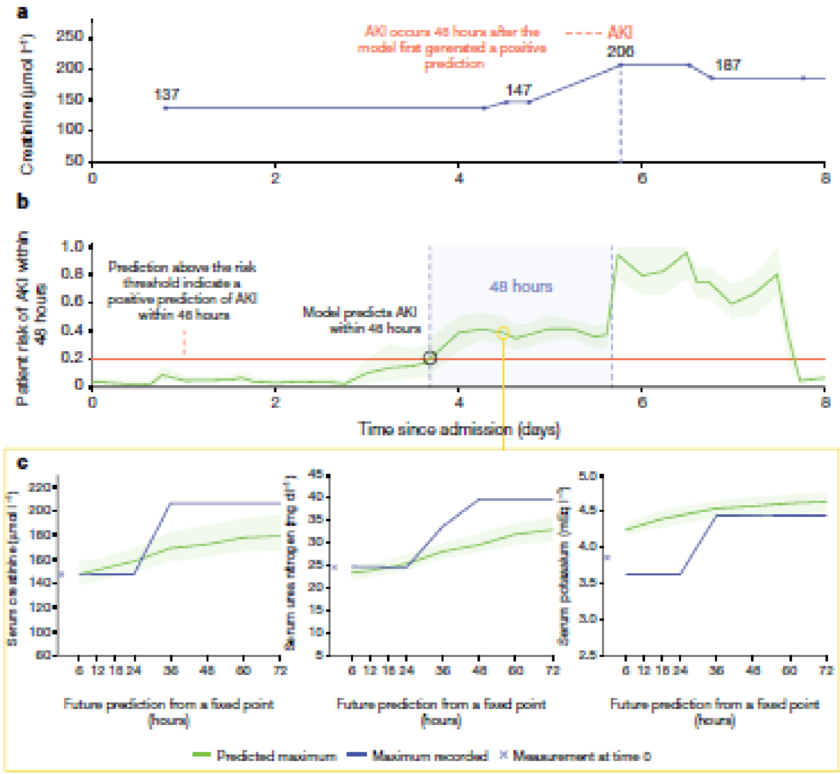
The hour of the day the test was ordered, the day of the week, and the amount of time between consecutive tests is more predictive of three year survival than the actual value of the test result, for most tests

LETTER

https://doi.org/10.1038/s41586-019-1390-1

A clinically applicable approach to continuous prediction of future acute kidney injury

Nenad Tomašev[1*], Xavier Glorot[1], Jack W. Rae[1,2], Michal Zielinski[1], Harry Askham[1], Andre Saraiva[1], Anne Mottram[1], Clemens Meyer[1], Suman Ravuri[1], Ivan Protsyuk[1], Alistair Connell[1], Cían O. Hughes[1], Alan Karthikesalingam[1], Julien Cornebise[1,12], Hugh Montgomery[3], Geraint Rees[4], Chris Laing[5], Clifton R. Baker[6], Kelly Peterson[7,8], Ruth Reeves[9], Demis Hassabis[1], Dominic King[1], Mustafa Suleyman[1], Trevor Back[1,13], Christopher Nielson[10,11,13], Joseph R. Ledsam[1,13*] & Shakir Mohamed[1,13]



Nephrol Dial Transplant (2019) 1–2
doi: 10.1093/ndt/gfz226

Nephrology Dialysis Transplantation

Prediction of acute kidney injury using artificial intelligence: are we there yet?

Wim Van Biesen [1,2], Jill Vanmassenhove[1] and Johan Decruyenaere[2,3]

[1]Renal Division, Ghent University Hospital, Ghent, Belgium, [2]Justifiable Digital Health Consortium, Ghent University Hospital, Ghent, Belgium and [3]Department of Intensive Care, Ghent University Hospital, Ghent, Belgium

RESEARCH

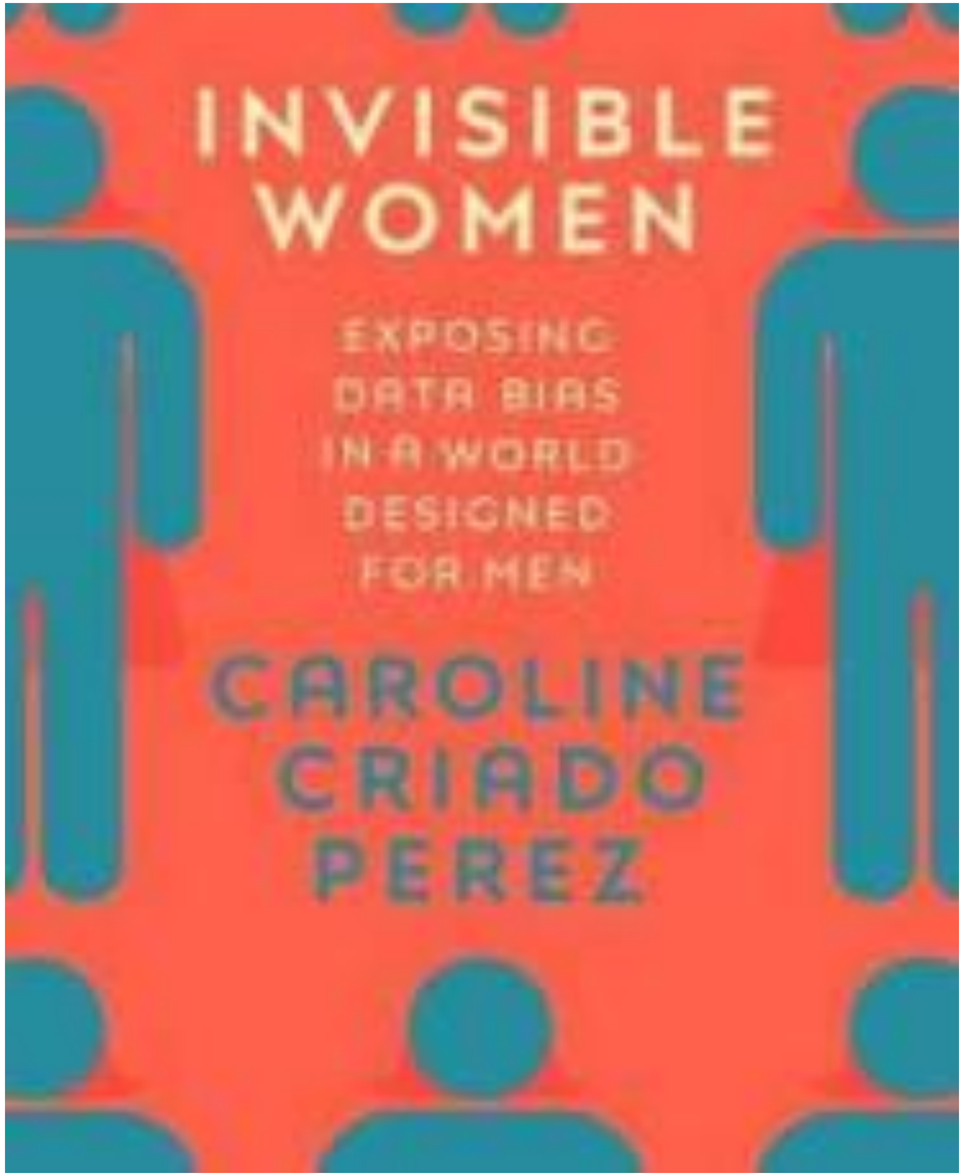
RESEARCH ARTICLE

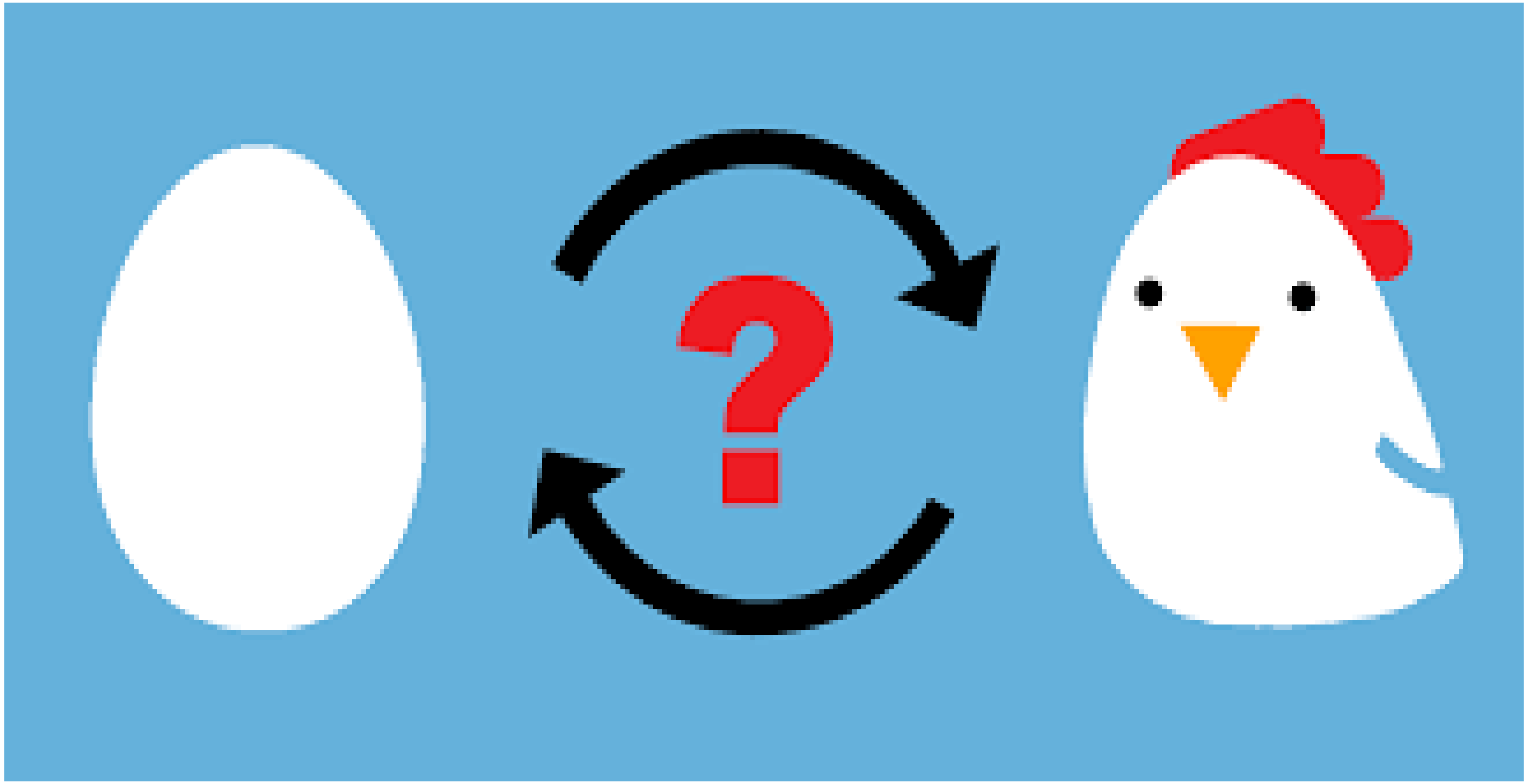
ECONOMICS

Dissecting racial bias in an algorithm used to manage the health of populations

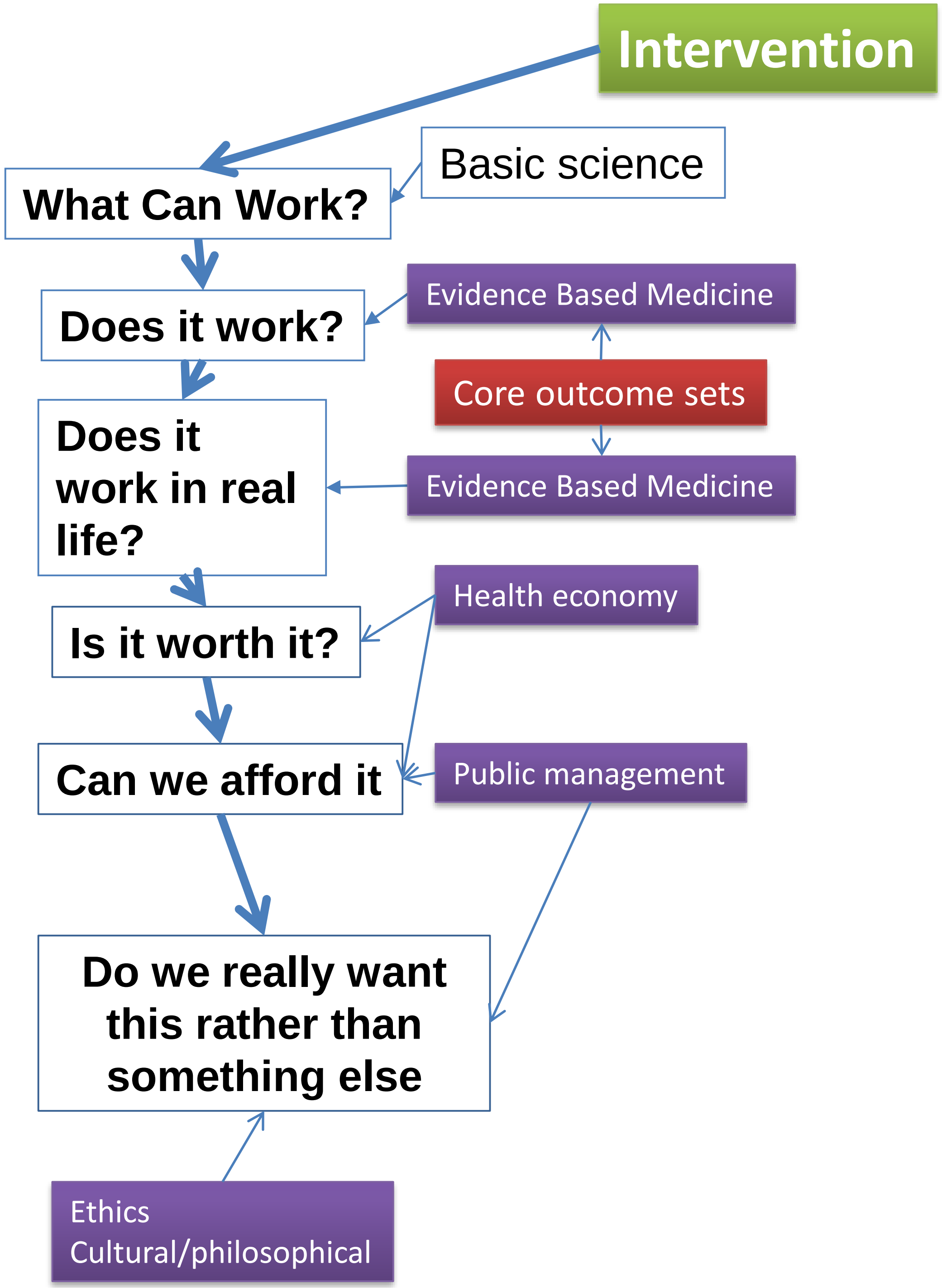
Ziad Obermeyer[1,2*], Brian Powers[3], Christine Vogeli[4], Sendhil Mullainathan[5*†]

Health systems rely on commercial prediction algorithms to identify and help patients with complex health needs. We show that a widely used algorithm, typical of this industry-wide approach and affecting millions of patients, exhibits significant racial bias: At a given risk score, Black patients are considerably sicker than White patients, as evidenced by signs of uncontrolled illnesses. Remedying this disparity would increase the percentage of Black patients receiving additional help from 17.7 to 46.5%. The bias arises because the algorithm predicts health care costs rather than illness, but unequal access to care means that we spend less money caring for Black patients than for White patients. Thus, despite health care cost appearing to be an effective proxy for health by some measures of predictive accuracy, large racial biases arise. We suggest that the choice of convenient, seemingly effective proxies for ground truth can be an important source of algorithmic bias in many contexts.





Causality


Intervention
What Can Work?
Basic science
Does it work?
Evidence Based Medicine
Core outcome sets
Does it work in real life?
Evidence Based Medicine
Health economy
Is it worth it?
Can we afford it
Public management
Do we really want this rather than something else
Ethics
Cultural/philosophical

Polysaccharide Conjugate Vaccine against Pneumococcal Pneumonia in Adults

M.J.M. Bonten, S.M. Huijts, M. Bolkenbaas, C. Webber, S. Patterson, S. Gault, C.H. van Werkhoven, A.M.M. van Deursen, E.A.M. Sanders, T.J.M. Verheij, M. Patton, A. McDonough, A. Moradoghli-Haftvani, H. Smith, T. Mellelieu, M.W. Pride, G. Crowther, B. Schmoele-Thoma, D.A. Scott, K.U. Jansen, R. Lobatto, B. Oosterman, N. Visser, E. Caspers, A. Smorenburg, E.A. Emini, W.C. Gruber, and D.E. Grobbee

49 vs 90 infection with vaccine type strain
100 vs 144 Pneumococcal CAP

Bonten et al, NEJM, 2015

Polysaccharide Conjugate Vaccine against Pneumococcal Pneumonia in Adults

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PER 84000 patients!!!!

49 vs 90 infection with vaccine type strai
100 vs 144 Pneumococcal CAP

NNT: 51/42000 => 1/823

Mortality from pneumococcal pneumonia: 2 vs 2

Overall mortality: 3006 vs 3005

Overall CAP: 747 vs 787

t al, NEJM, 2015

How much does Herceptin cost?

28000 euro/year

Primary endpoint effect size: disease free survival at 2 year:

7,6 %(85,5% vs 78,2%).

Table 1 Cost and potential benefits of adjuvant cancer treatments in Norfolk and Norwich University Hospital Trust

Treatment	No of patients given treatment	Drug cost (£000)	Proven benefit	Potential benefit at our hospital	Cost per patient cured (£000)
Adjuvant chemotherapy for lung cancer	15	23	5-15% improved 5 year overall survival[w3]	1 extra patient cured	23
Oxaliplatin as adjuvant therapy for colon cancer compared with fluorouracil alone	20	137	5% improved 3 year disease-free survival; no benefit to overall survival[w4]	1 extra patient without recurrence at 3 years	137
Neoadjuvant chemotherapy for oesophageal cancer	25	8	9% improved 5 year survival[w5]	3 extra patients cured	2.67
Rituximab in addition to CHOP for non-Hodgkin lymphoma in patients over 60	25	215	13% improved 2 year overall survival[w6]	3 extra patients cured	71.67
Adjuvant aromatase inhibitors in postmenopausal breast cancer	270	120	3.7% improved disease-free survival compared with tamoxifen; no benefit to overall survival[w7]	8 extra patients without recurrence at 5 years	15
Total	355	503		16 extra patients cured	
Herceptin for early stage breast cancer	75	1940	0-4% improved 4 year overall survival[w1 w2]	3 extra patients cured	650

CHOP=cyclophosphamide, doxorubicin, vincristine, and prednisolone.

Barett et al, BMJ, 2006

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Remote digital monitoring of medication intake: methodological, medical, ethical and legal reflections

Wim Van Biesen, Johan Decruyenaere, Katerina Sideri, Julian Cockbain & Sigrid Sterckx

To cite this article: Wim Van Biesen, Johan Decruyenaere, Katerina Sideri, Julian Cockbain & Sigrid Sterckx (2019): Remote digital monitoring of medication intake: methodological, medical, ethical and legal reflections, Acta Clinica Belgica, DOI: 10.1080/17843286.2019.1708152

To link to this article: https://doi.org/10.1080/17843286.2019.1708152

INSURANCE SOLIDARITY

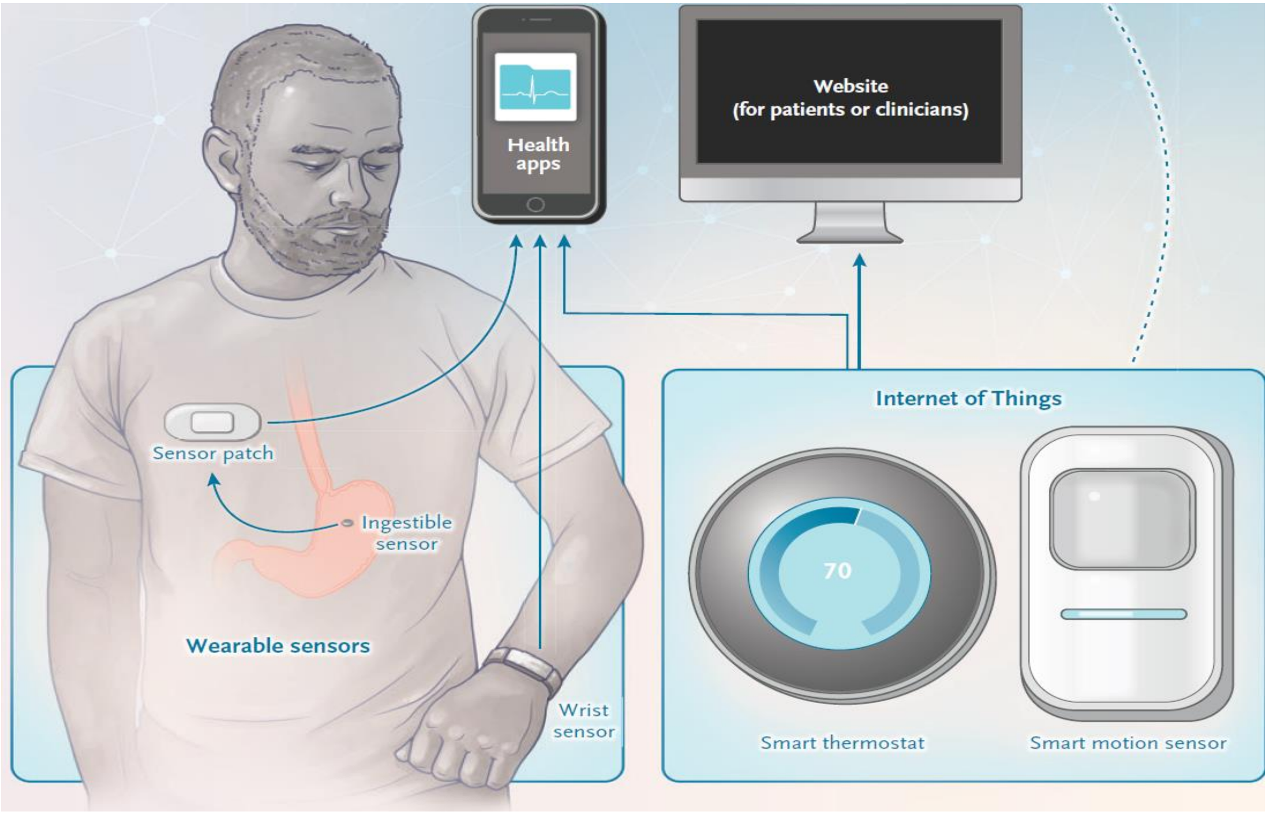
The NEW ENGLAND JOURNAL of MEDICINE

REVIEW ARTICLE

FRONTIERS IN MEDICINE

Mobile Devices and Health

Ida Sim, M.D., Ph.D.



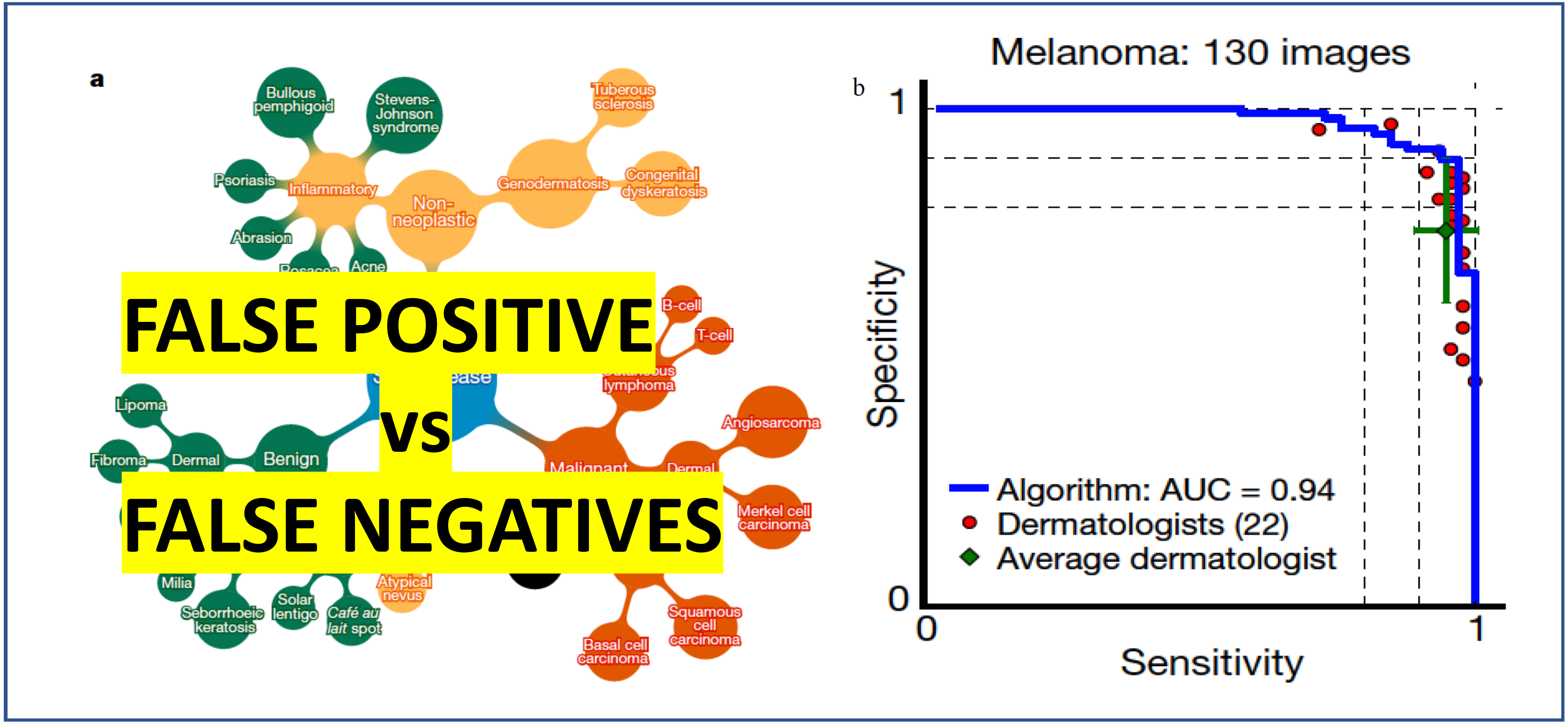


Figure 3: a) (left panel) Illustration of the top levels of the tree-structured taxonomy. The full set of 2032 diseases are leaf nodes and were used for the developing the algorithm. b) (right panel) Classification results for a set of 130 images of melanocytic lesions, blue curve from the algorithm, red dots from individual dermatologists. Images taken from Esteva et al. 2017 [30].

EDITORIALS

Check for updates

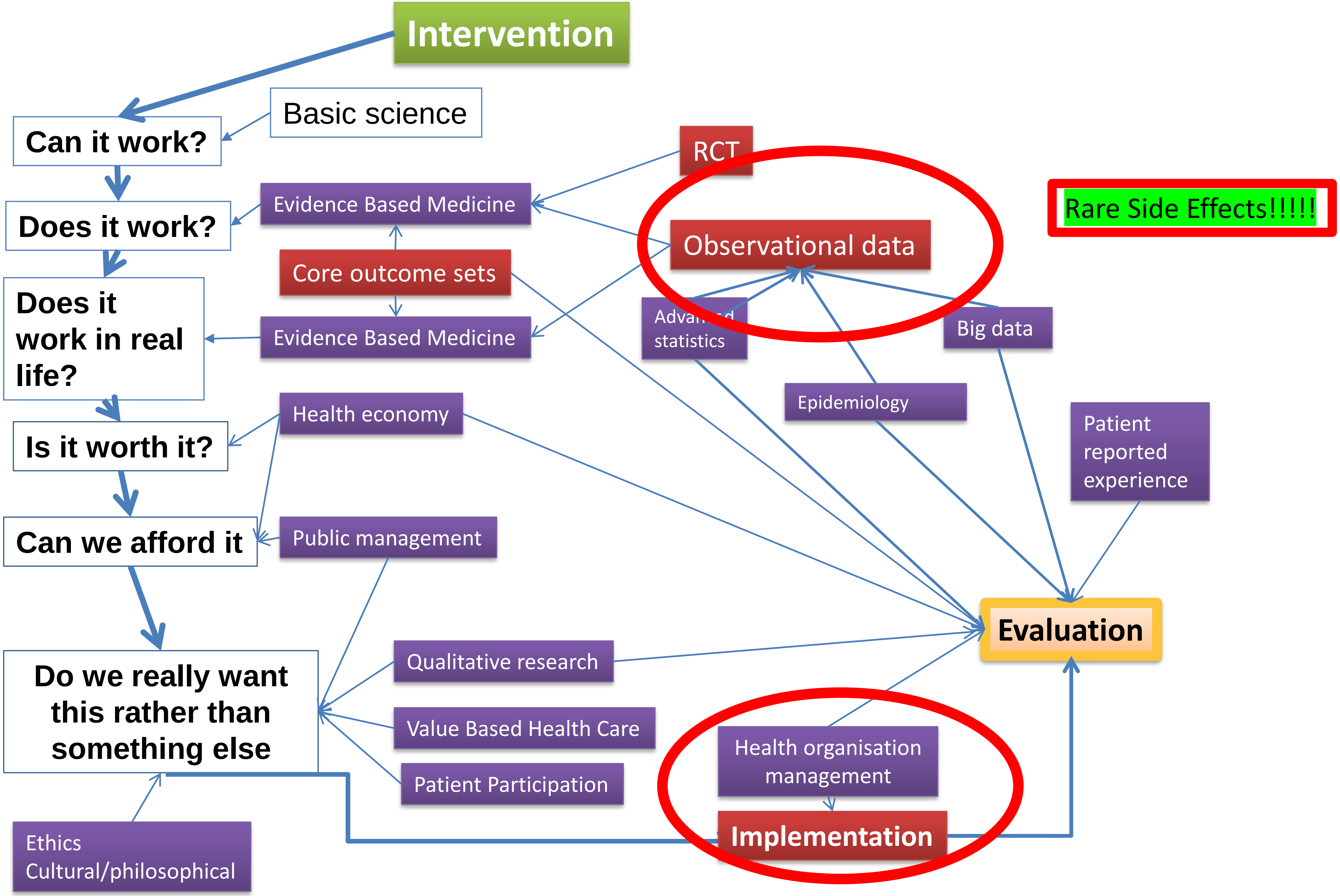
General practice by smartphone

GP at Hand risks destabilising care for patients with the greatest need

Martin Roland *emeritus professor of health services research*

University of Cambridge, Cambridge, UK

"You can't list your iPhone as your primary-care physician."



Intervention
Basic science
Can it work?
Does it work?
Does it work in real life?
Is it worth it?
Can we afford it
Do we really want this rather than something else
Evidence Based Medicine
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Evidence Based Medicine
Health economy
Public management
Qualitative research
Value Based Health Care
Patient Participation
Ethics
Cultural/philosophical
RCT
Observational data
statistics
Big data
Epidemiology
Rare Side Effects!!!!!
Patient reported experience
Evaluation
Health organisation management
Implementation

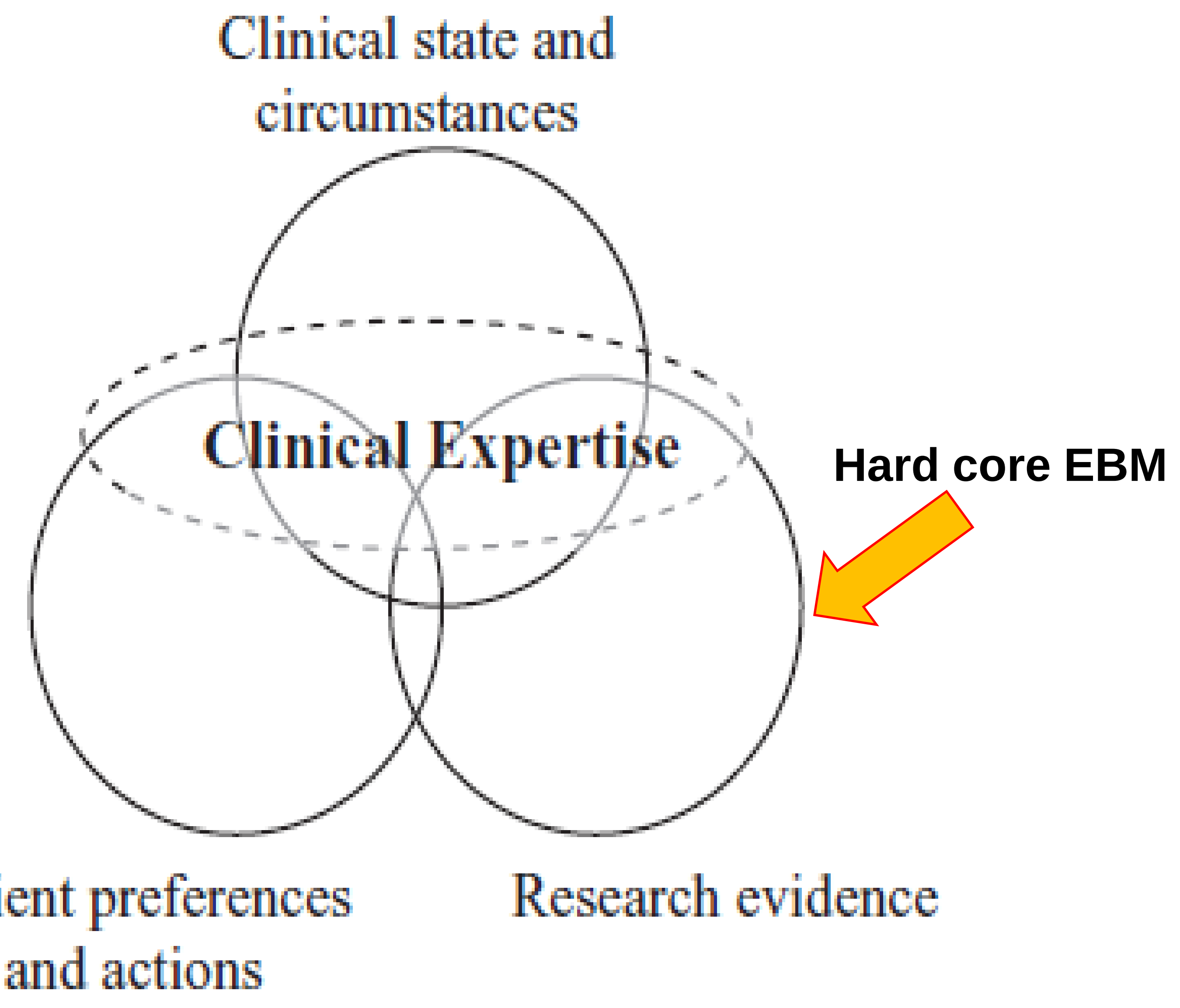
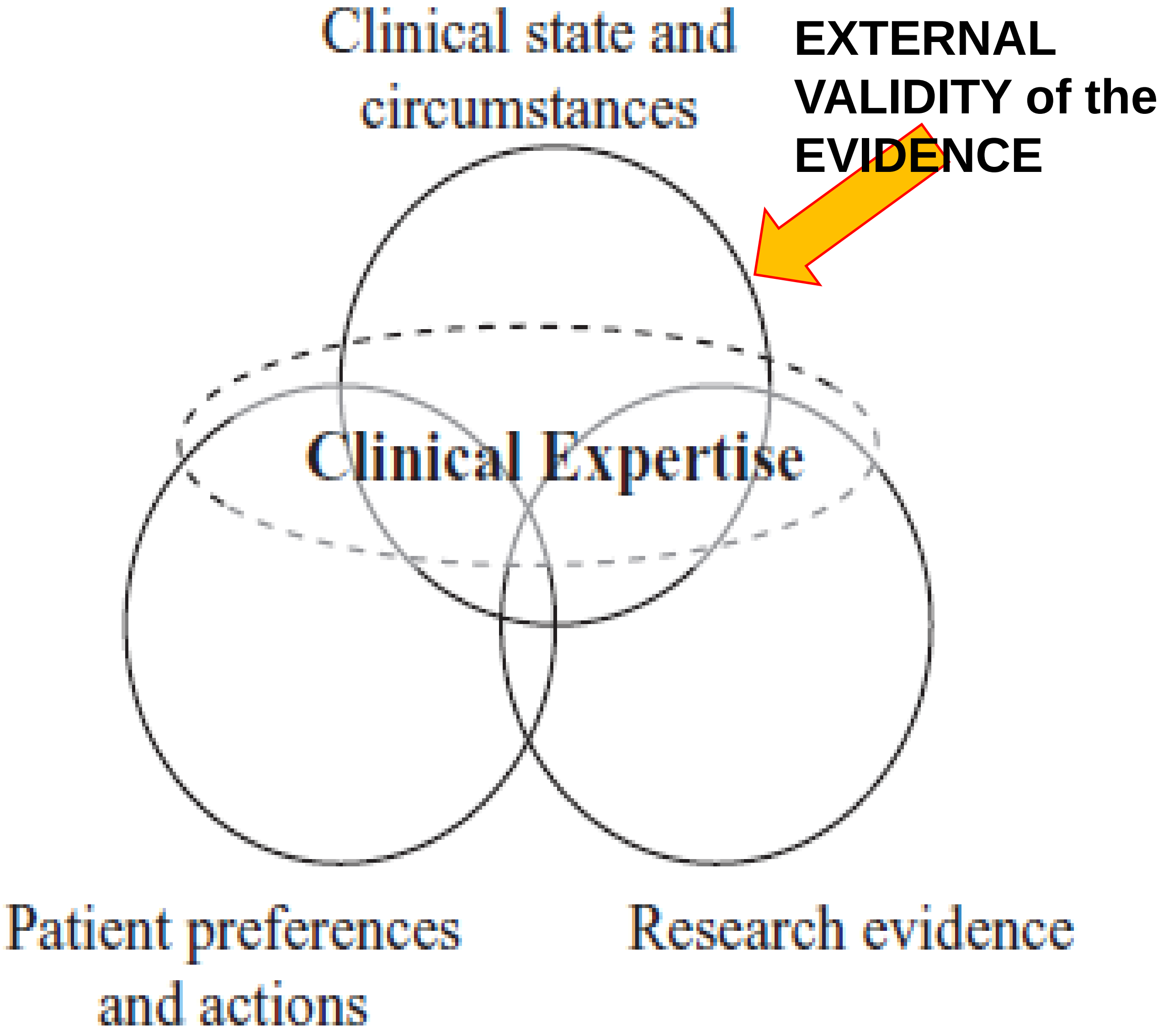


Figure 1 Evidence-based decision-making for clinical contexts.



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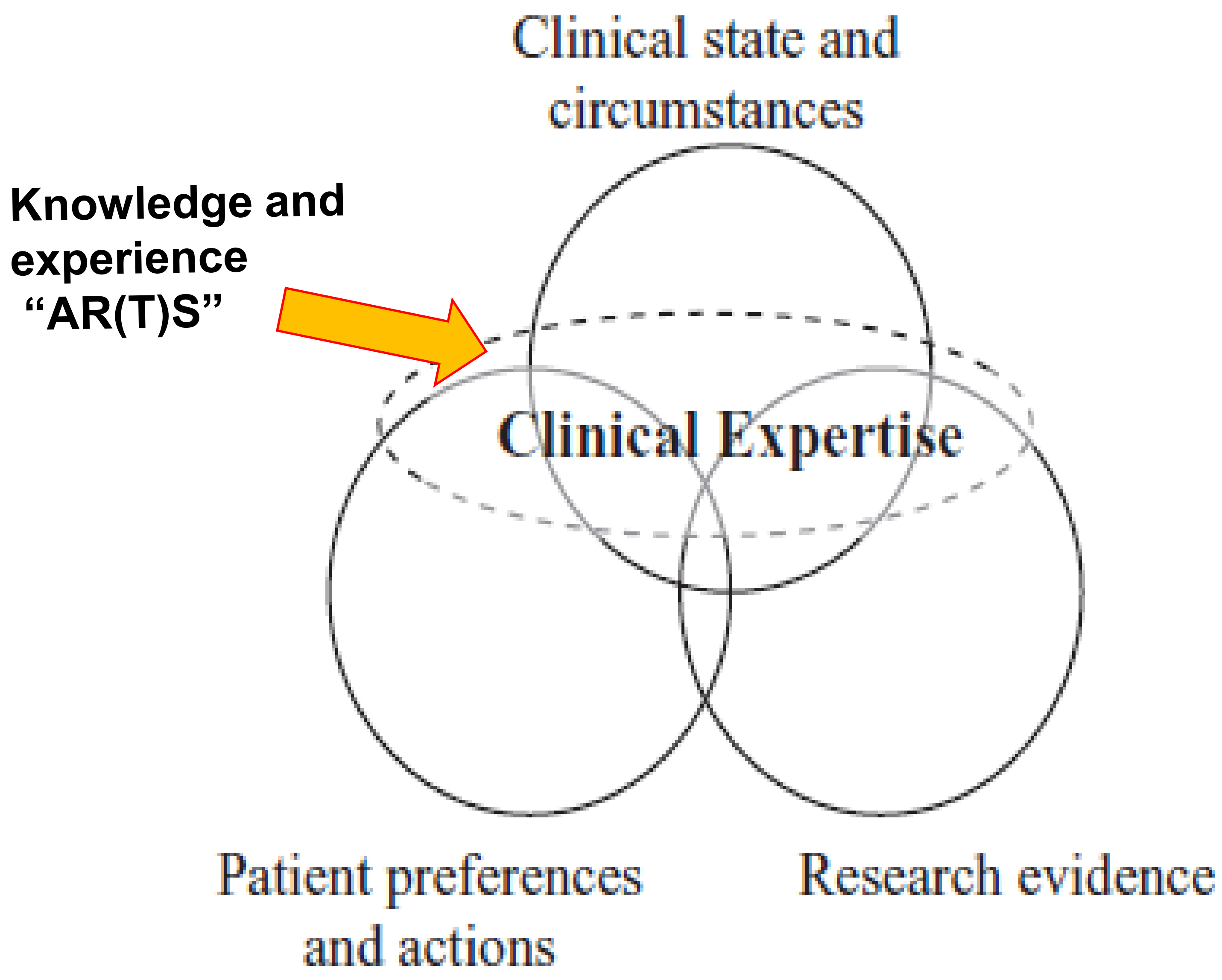

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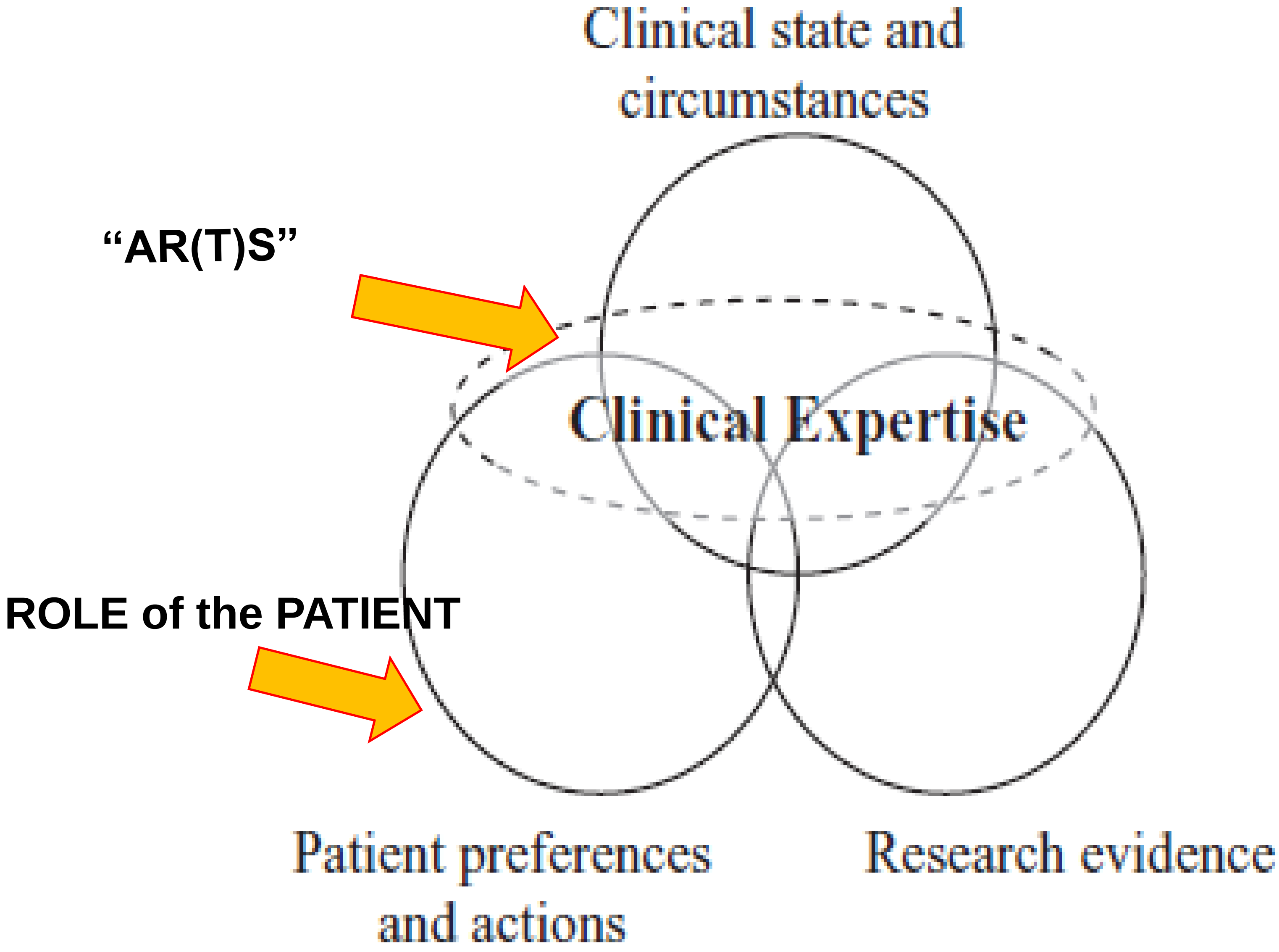

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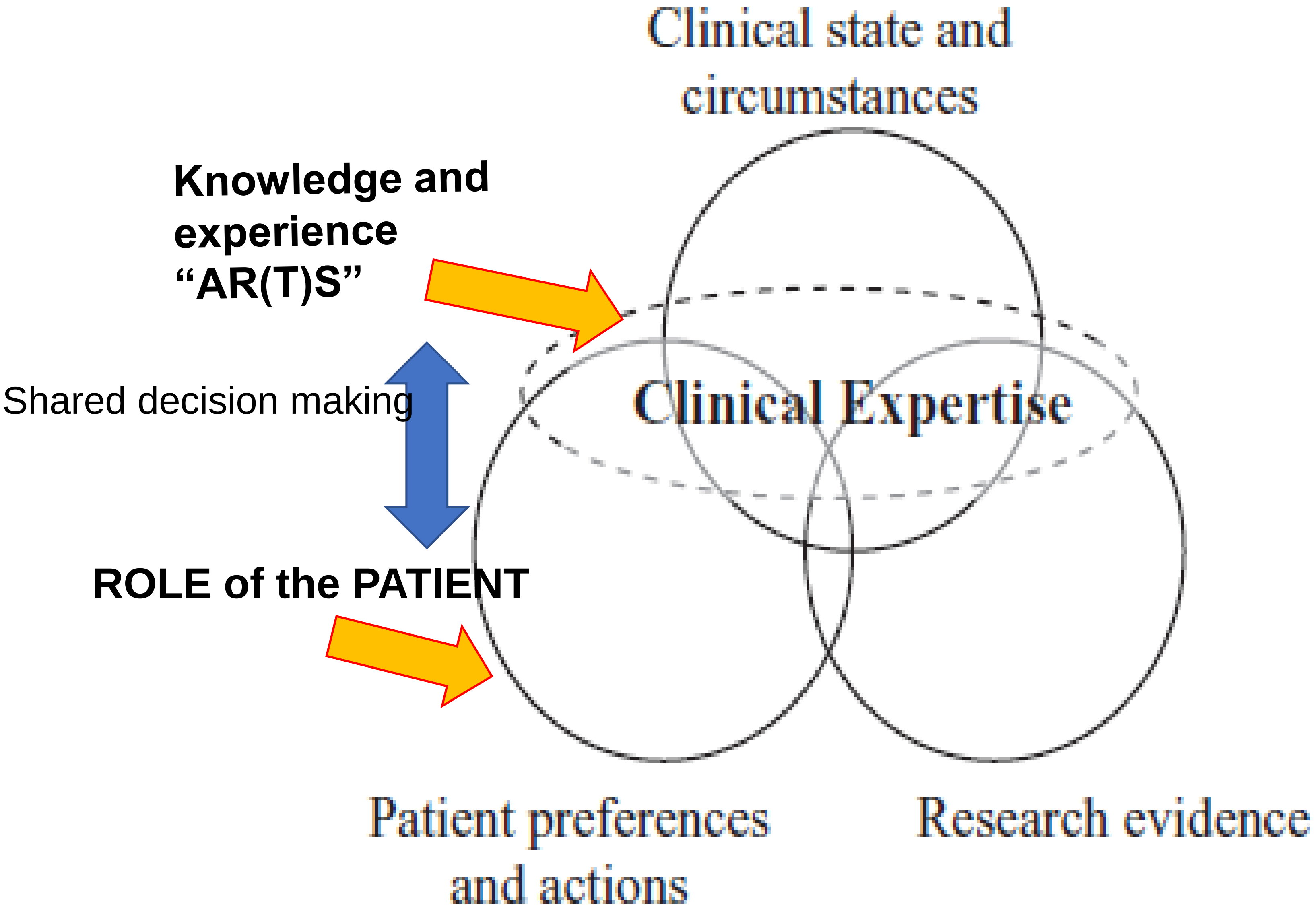
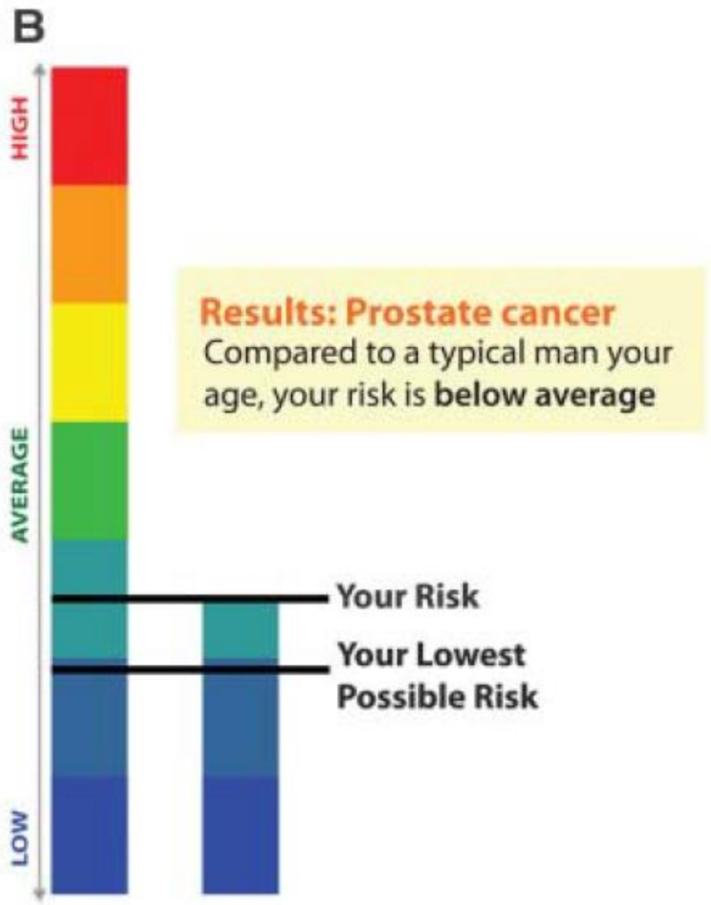
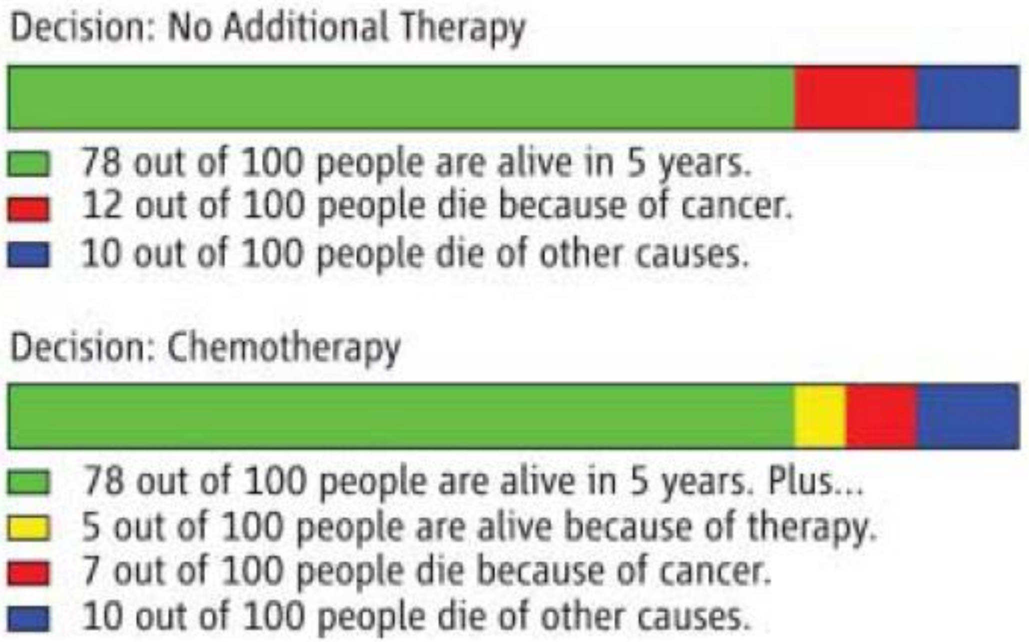


Figure 1 Evidence-based decision-making for clinical contexts.

Visualizing Uncertainty About the Future

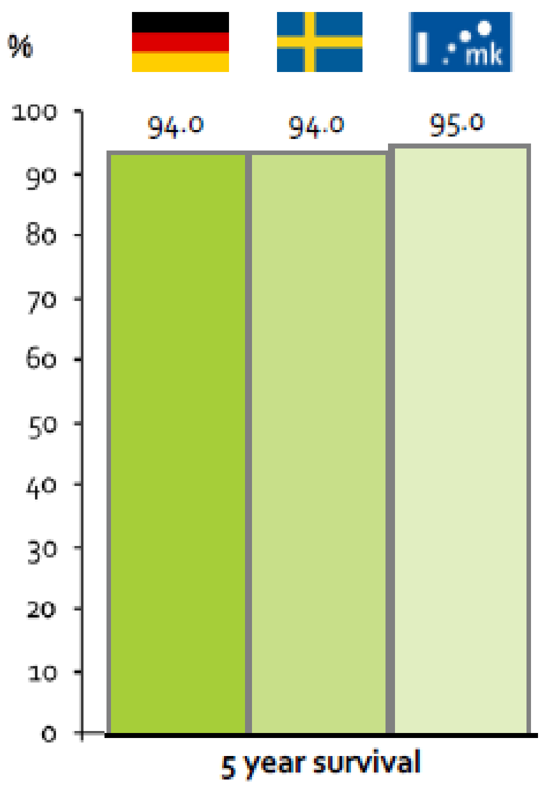
David Spiegelhalter,[1*] Mike Pearson,[1] Ian Short[2]





This is why measuring and reporting meaningful outcomes matters Comparing outcomes of prostate cancer care

Focussing on mortality alone…



Germany Sweden Best-in-class: Martini Klinik

Swedish data rough estimates from graphs; Source: National quality report for the year of diagnosis 2012 from the National Prostate Cancer Register (NPCR) Sweden, Martini Klinik, BARMER GEK Report Krankenhaus 2012, Patient-reported outcomes (EORTC-PSM), 1 year after treatment, 2010

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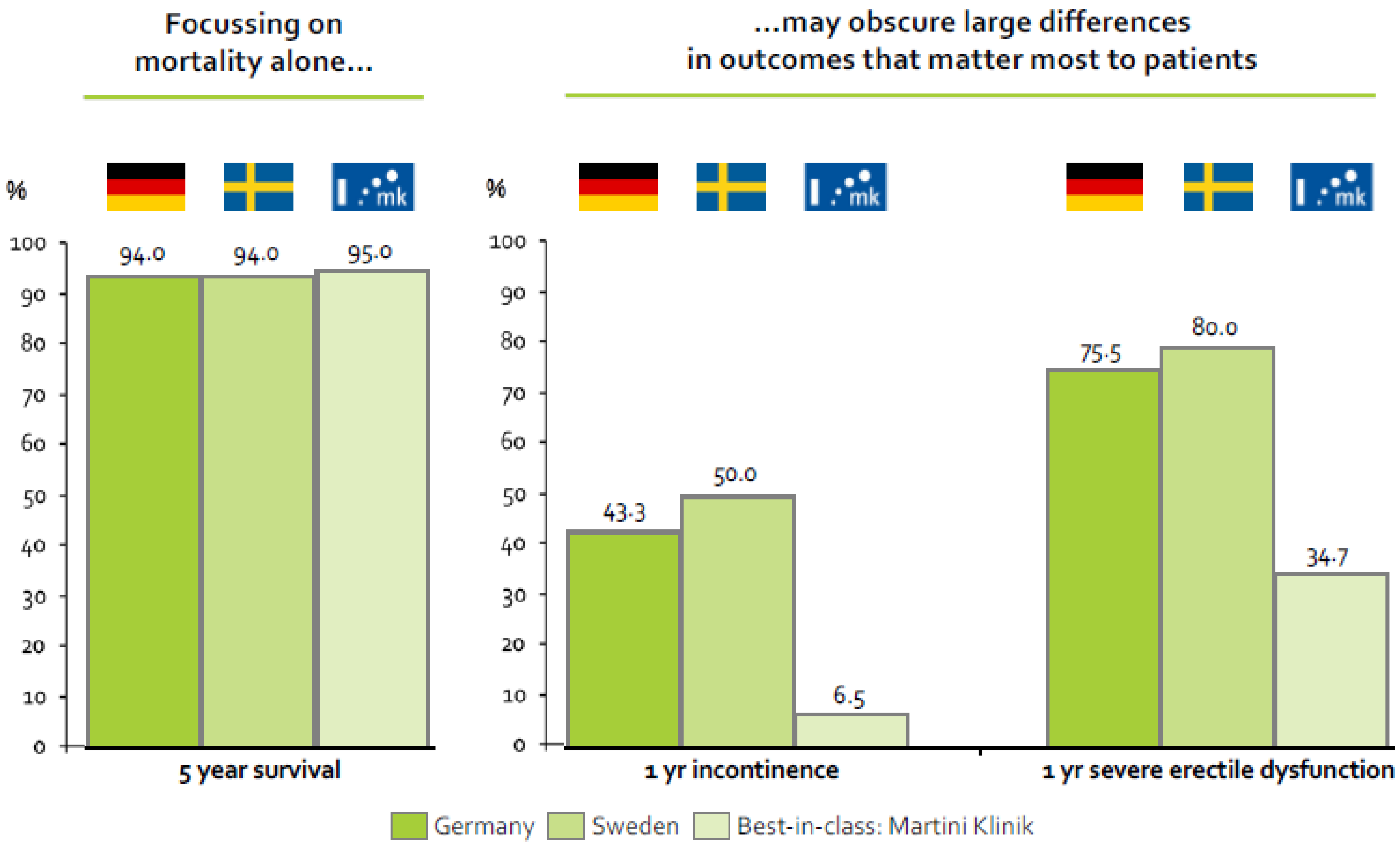

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Computer knows best? The need for value-flexibility in medical AI

Rosalind J McDougall

Annals of Internal Medicine

A Counterintuitive Tool for Connected Care

Zuzanna Czernik, MD; Robert Chang, MD; and Vineet Chopra, MD, MSc

A young man with recently diagnosed HIV was ad-

consultants. Viewing the EMR together empowers the