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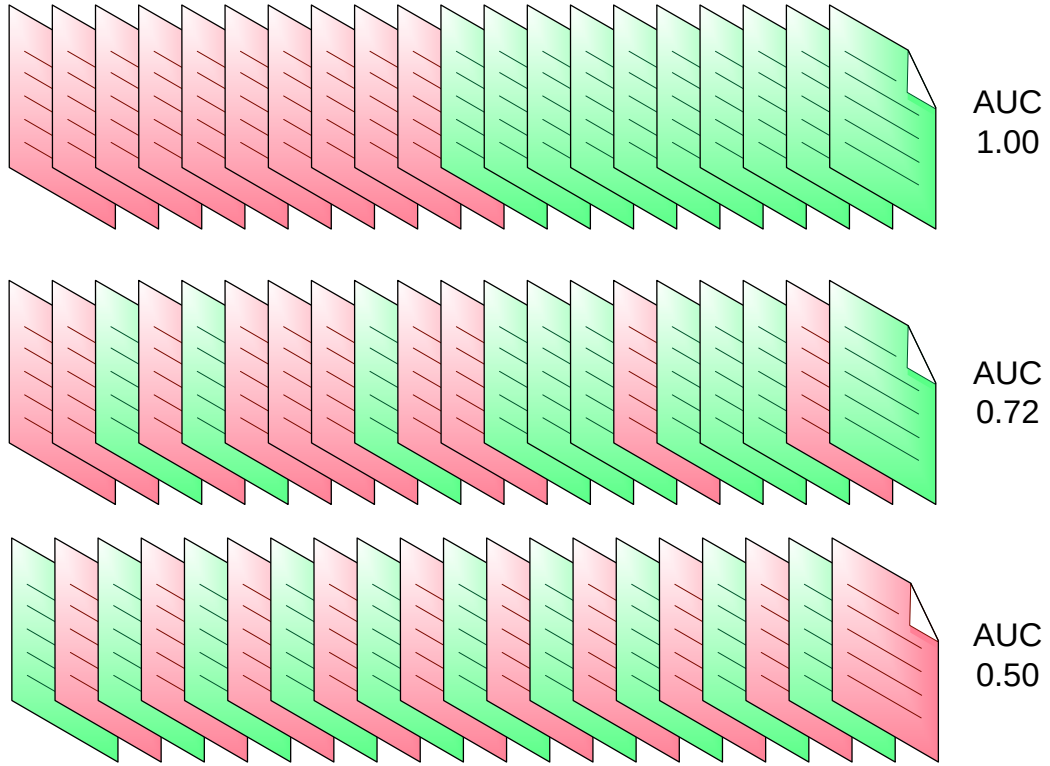
Trust in AI in Health Care: Opportunities rather than Risks

Andre Dekker
Medical Physicist | Professor of Clinical Data Science

Maastricht UMC+ | Maastricht University | Maastro Clinic

4th ISACA Risk Event
Responsible AI | Podium II | Bussum | November 16, 2023 | 15:10-15:55

Prediction of survival

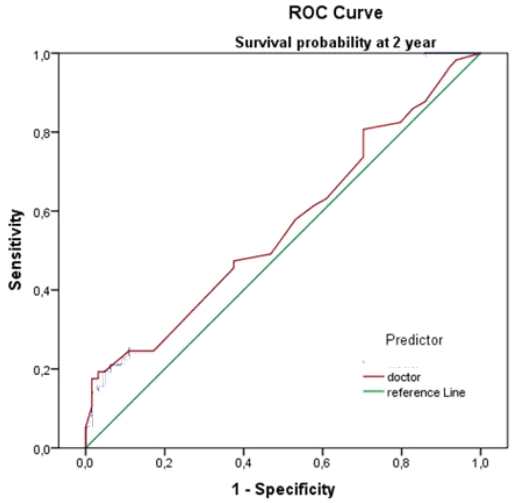


Less likely to survive

More likely to survive

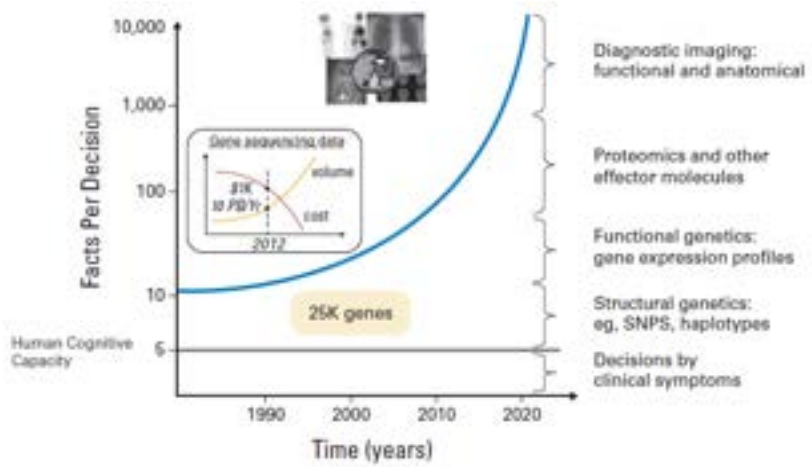
Actual survival

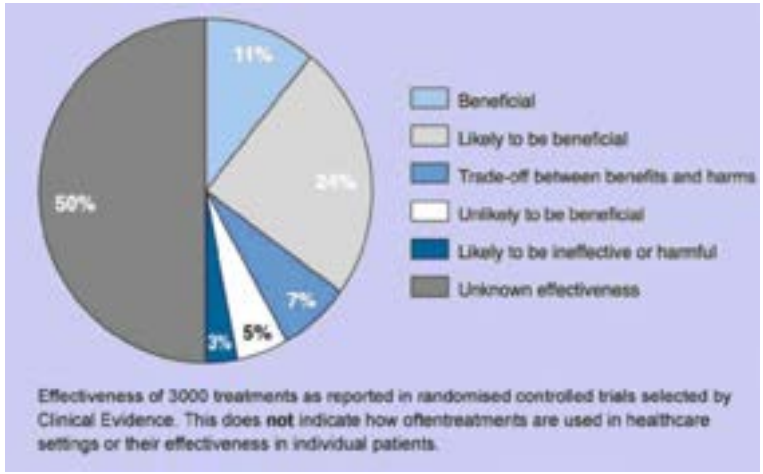
Hey, ~~ChatGPT~~ Doctor: can I trust you?



Lung Cancer
2 year survival
158 patients
5 MDs
Prospective
AUC: 0.56

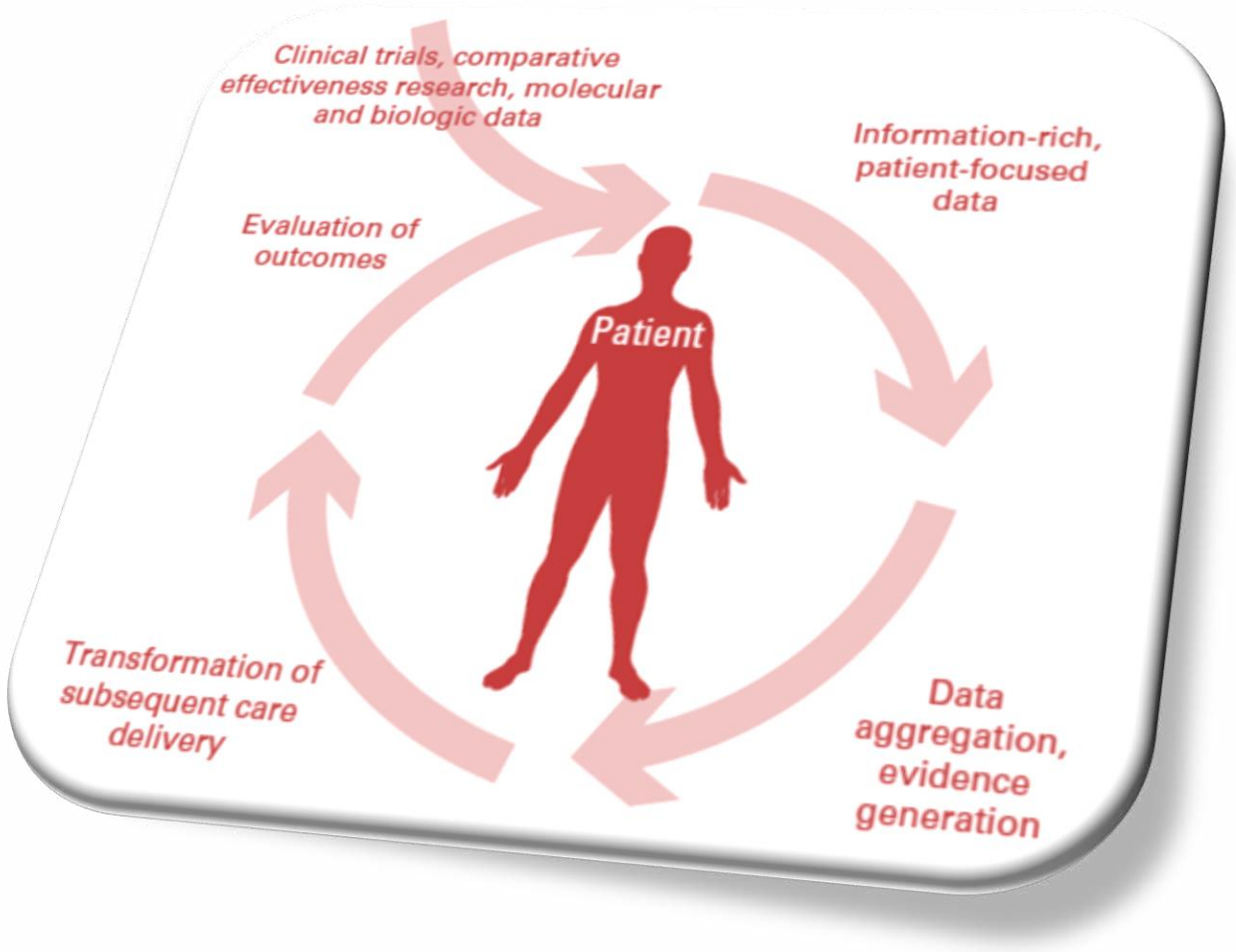
- Explosion of data
- Explosion of decisions
- Explosion of 'evidence'
  - Too much to read
  - 3 % in trials, bias
  - Sharp knife





Oberije et al. , Radiother Oncol. 2014; 112: 37–43 / J Clin Oncol 2010;28:4268 / JMI 2012 Friedman, Rigby / BMJ Clinical Evidence

Potential of Artificial Intelligence
Learning Health Care System – Faster Innovations & Better Outcomes



J Clin Oncol 2010;28:4268

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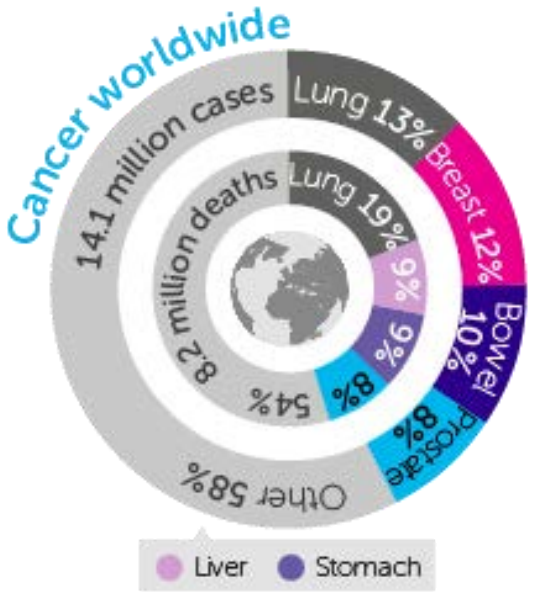
Data

Big Data? – An example from cancer



Oncology
2007-2017
150M patients
0.1-10GB per patient

15-1500PB
80% unstructured

Hospitals
China: 25.000
India: 35.000
Germany: 2.000
France: 2.300
Italy: 1.100
USA: 5.500
Australia: 1.400

TOTAL ~100.000

Barriers to sharing data

[..] the problem is not really technical […]. Rather, the problems are **ethical, political, and administrative**.
Lancet Oncol 2011;12:933

1. Administrative (I don't have the resources)
2. Political (I don't want to)
3. Ethical (I am not allowed to)

4. Technical (I can't)

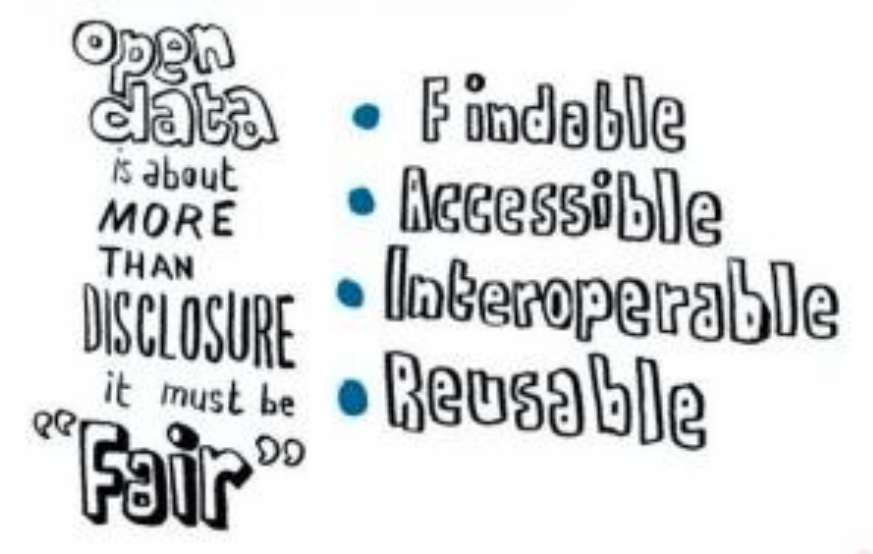
A different approach

If sharing is the problem: Don't share the data

If you can't bring the data to the research
You have to bring the research to the data

Challenges

- The research application has to be distributed (trains & track)
- The data has to be understandable by an application (i.e. not a human) -> FAIR data stations



www.personalhealthtrain.nl

PERSONAL HEALTH TRAIN

health RI
enabling data driven health & life sciences

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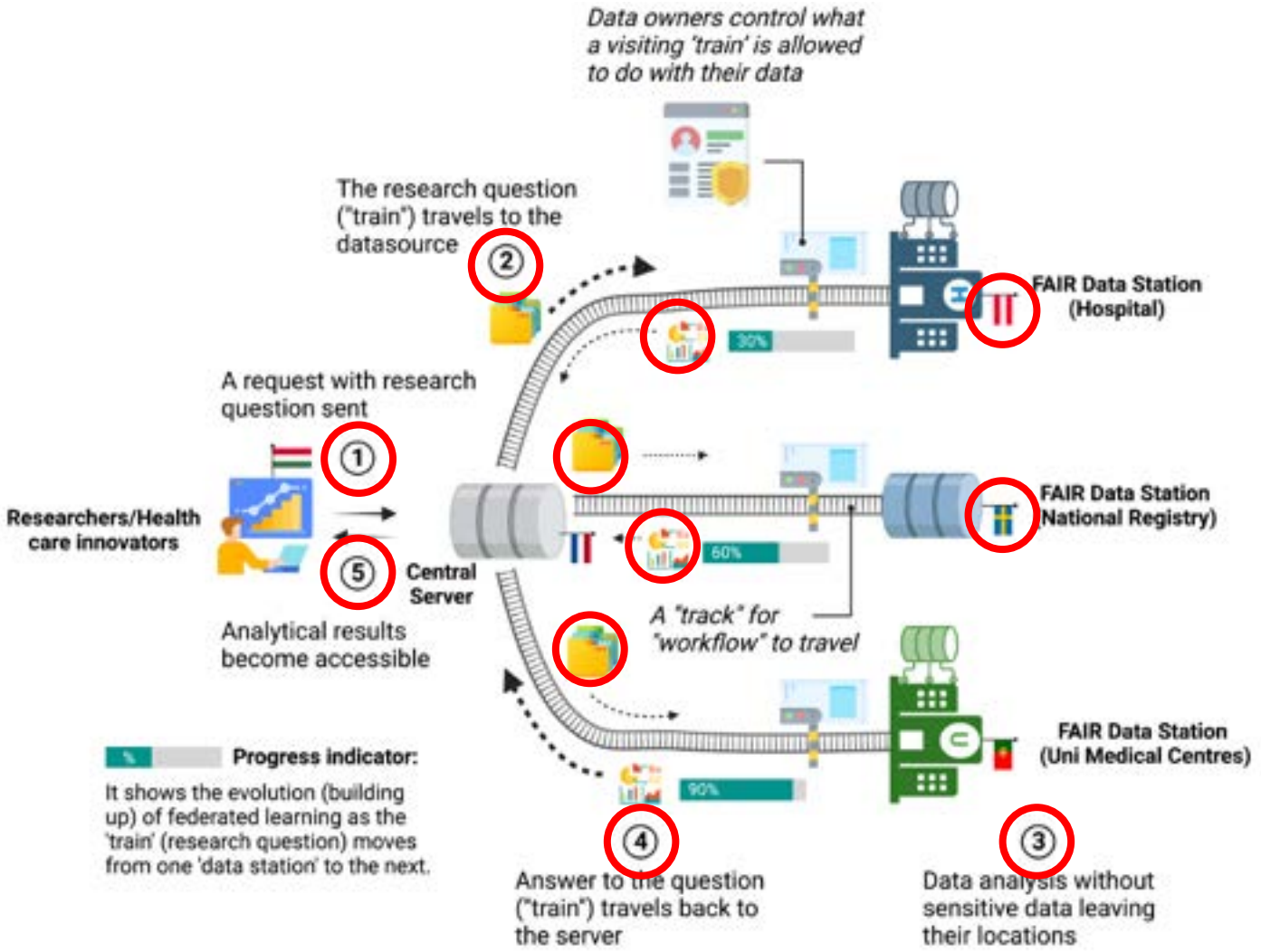
Wilkinson, DOI: 10.1038/sdata.2016.18

Personal Health Train (2015)

Federated FAIR Data and Learning Infrastructure



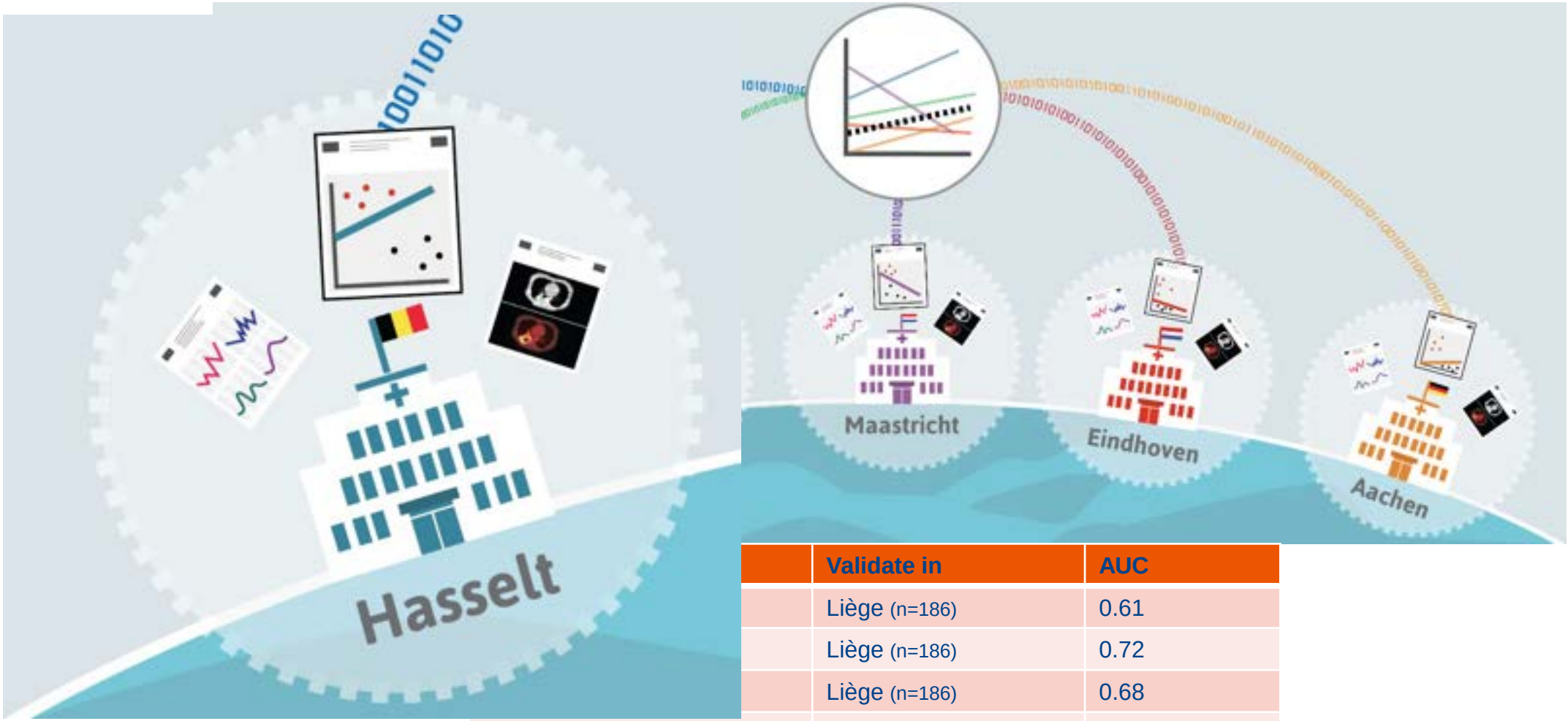
Simple example

Brussels	Frankfurt	Maastricht	Oslo	Leeds	Milan
87	62	83	46	70	76
69	69	56	49	90	64
	47	72	56	93	73
	73	84	95	72	
	59	63	58	60	
	49		72	47	
	62		53	62	
			81	94	
			73		

N=34
Mean Age = 68.2y

$$\frac{2 \times 78.0 + 7 \times 60.1 + 5 \times 71.6 + 9 \times 64.8 + 8 \times 73.5 + 3 \times 71.0}{2 + 7 + 5 + 9 + 8 + 3} = 68.2$$

euroCAT example



	Validate in	AUC
	Liège (n=186)	0.61
	Liège (n=186)	0.72
	Liège (n=186)	0.68
Maastricht (n=52)	Liège (n=186)	0.75
All 4 together (n=136)	Liège (n=186)	**0.77**
All 5 together (n=322)	World (n=*inf*)	?

Hasselt
Eindhoven
Maastricht
Liège
Nijmegen
Amsterdam
Rotterdam
Zwolle
Groningen
Tilburg
Leuven
Utrecht
Oslo
Bergen
Poznan
Odense
Aarhus
Aachen
Nicosia
Frankfurt
Lisbon
Rome
Brussels
Vejle
Paris
Lyon
Warsaw
Milan
Basel
Zurich
Stockholm
Vienna
Munich
Budapest
Copenhagen
Cardiff
Manchester
Leeds
Sheffield
Oxford
Cambridge
Hull

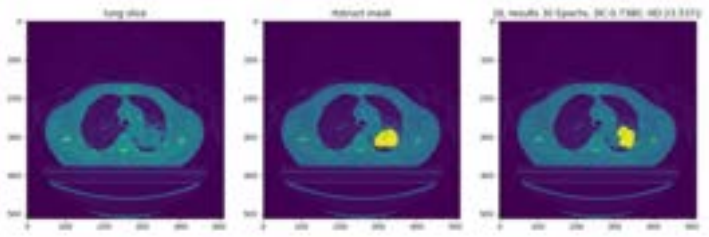
Ottawa
Toronto
Boston
Houston
Philadelphia
Ann Arbor
Tampa
Seattle
Burlington
Baltimore

Seoul
Shanghai
Suining
Tianjin
Shantou
Guangzhou
Hangzhou

Vellore
Hyderabad
Chennai

Liverpool
Westmead
Newcastle
Coffs Harbour
Wollongong

São Paulo
Bloemfontein
Arba Minch



Open Source (vantage6): distributedlearning.ai

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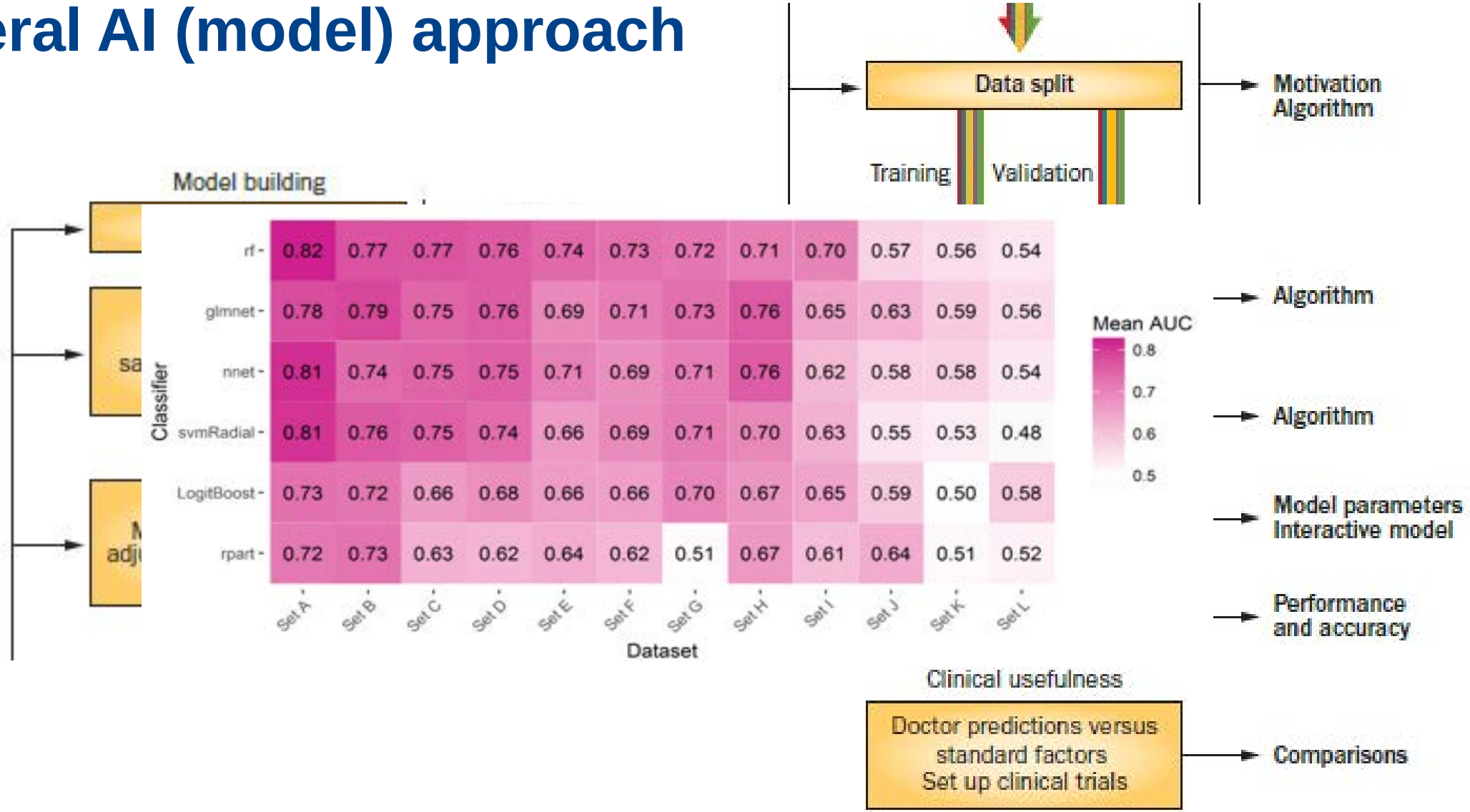
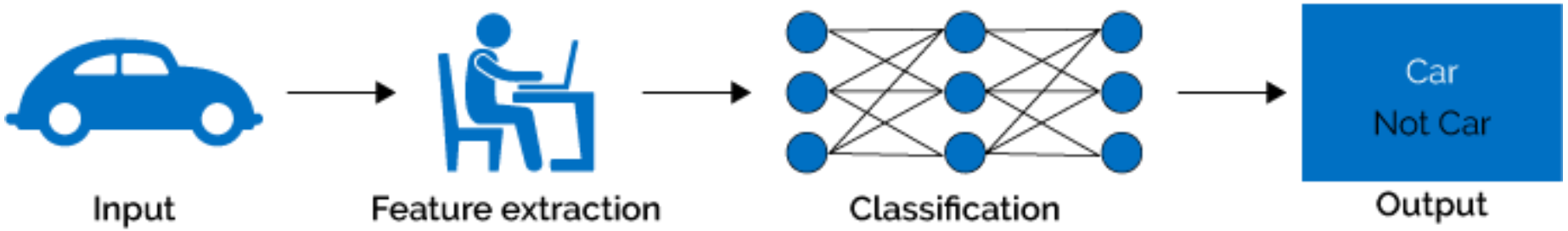
Learning

General AI (model) approach

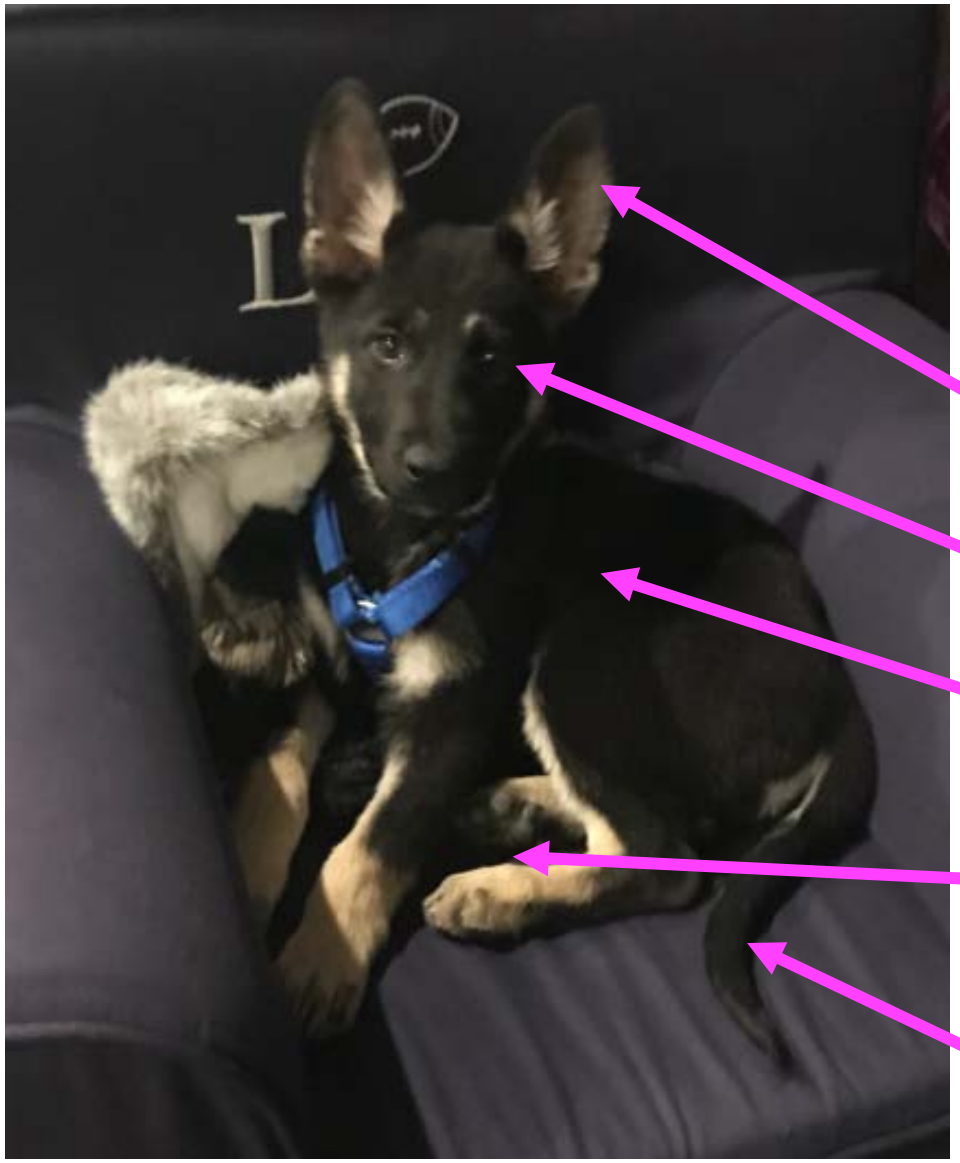


Machine Learning



Slide courtesy of Kristy Brock

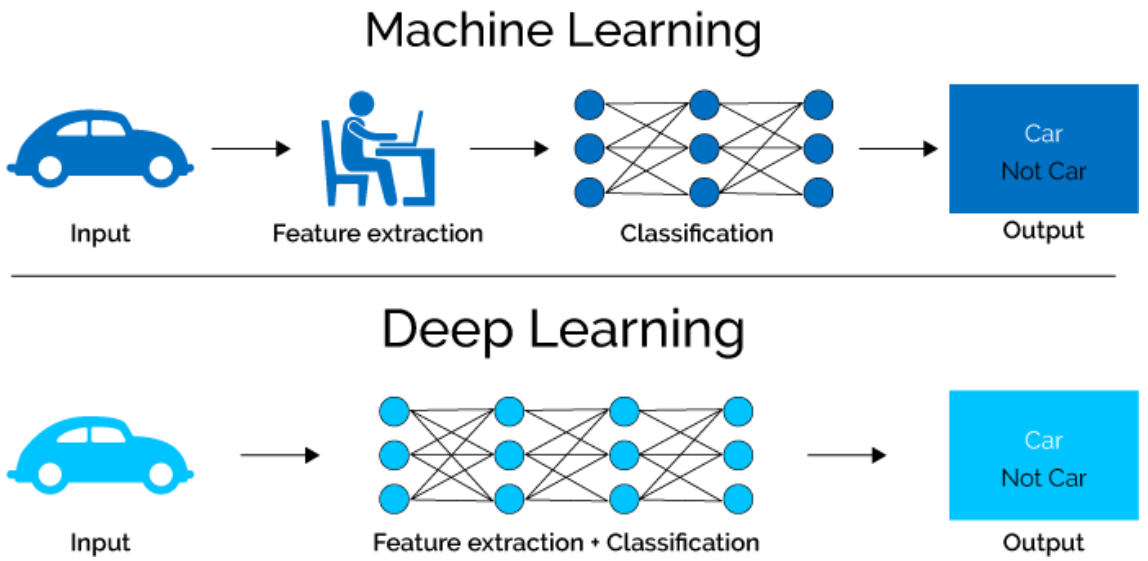
Slide (and dog) courtesy of Kristy Brock



NOT A CAT!

Cat: 97%

Deep Learning – Human out of the loop



Slide courtesy of Kristy Brock

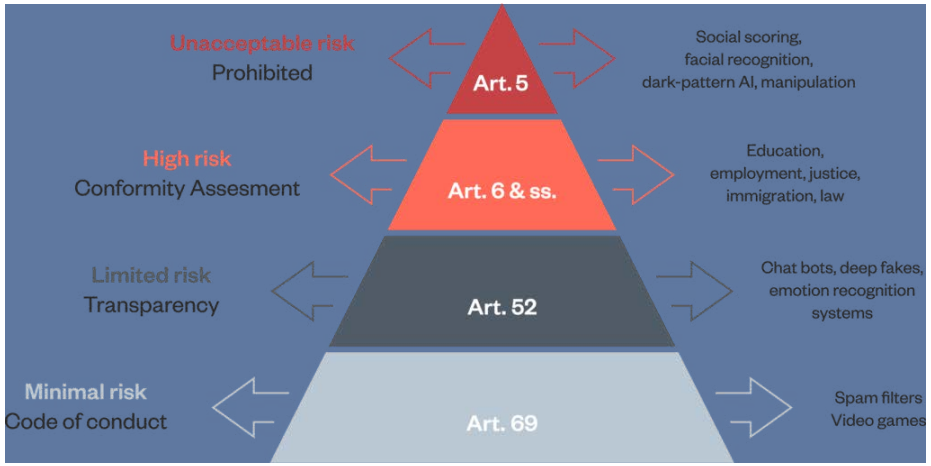
Regulatory & Contracts

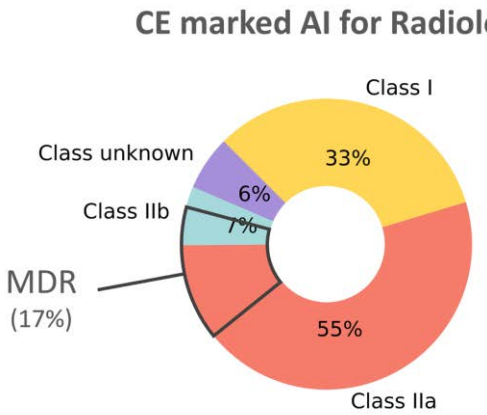
EUROPEAN HEALTH DATA SPACE
#EUDigitalHealth

Nat Biomed Eng 2018;2:719

Table 3 | Comparisons between human evaluations and different types of AI approaches

Approaches	Model comprehensibility	Performance	Reproducibility	Dependency on prior knowledge	Development and training costs[a]	Running costs	Around-the-clock availability	Update costs
Human evaluation	High	Moderate or high	Moderate	High	High	High	Low	High
Rule-based algorithms	High	Moderate or high	High	High	Moderate or high	Low	High	High
Feature-based machine-learning methods	Moderate or high	Moderate or high	High	Moderate[b]	Moderate	Low	High	Moderate[c]
Deep artificial neural networks	Low or moderate	High	High	Low	Moderate	Low	High	Low





"If the transition to the MDR continues at this pace, half of the AI products for radiology can no longer be used clinically after May 2024."

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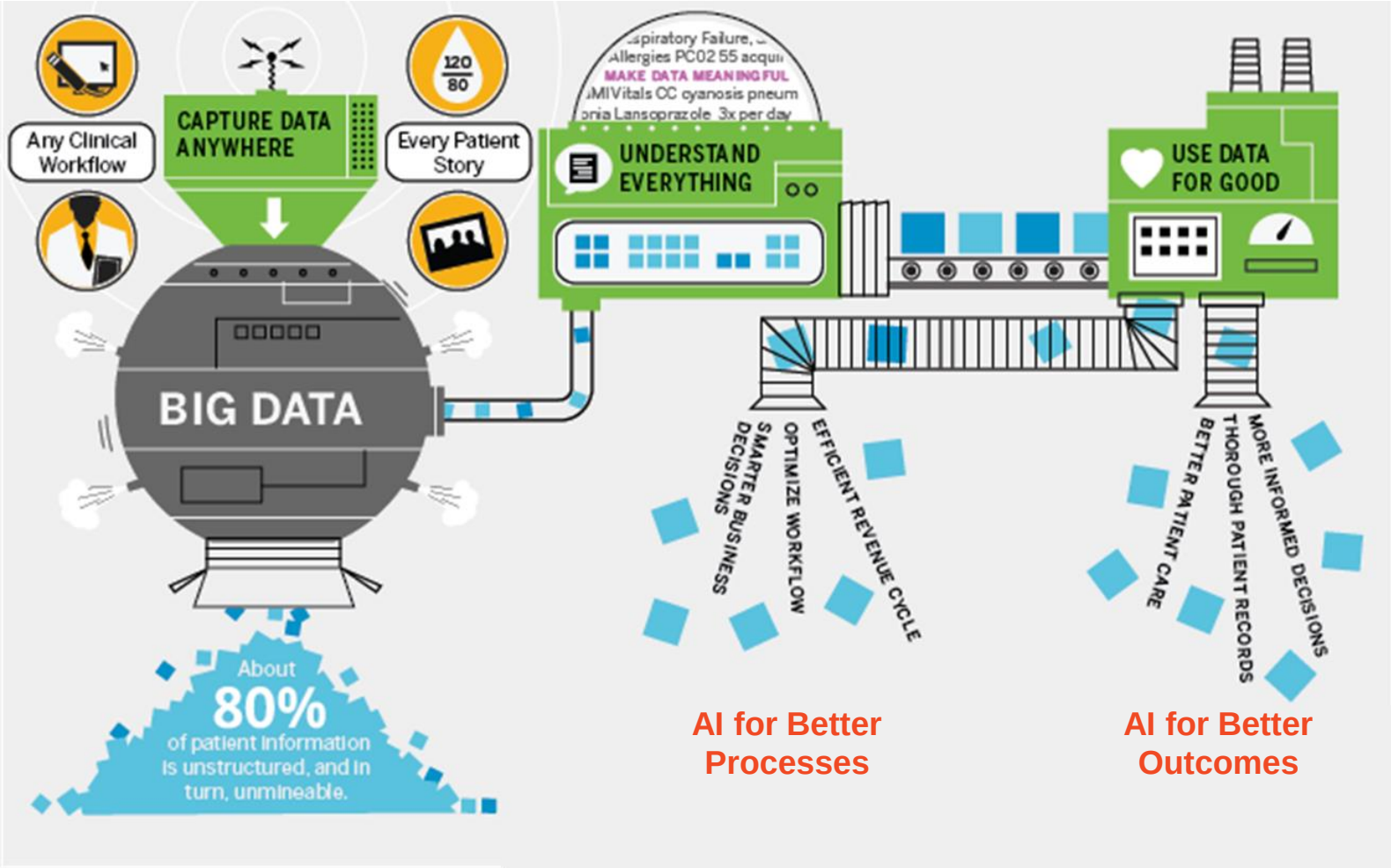
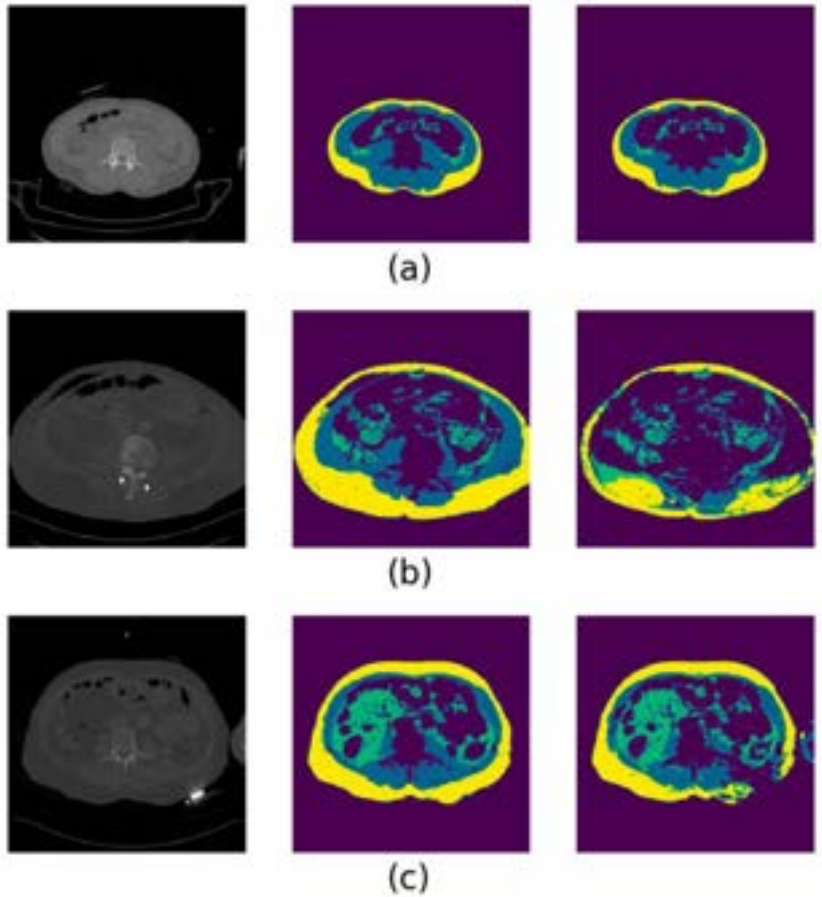
Applications

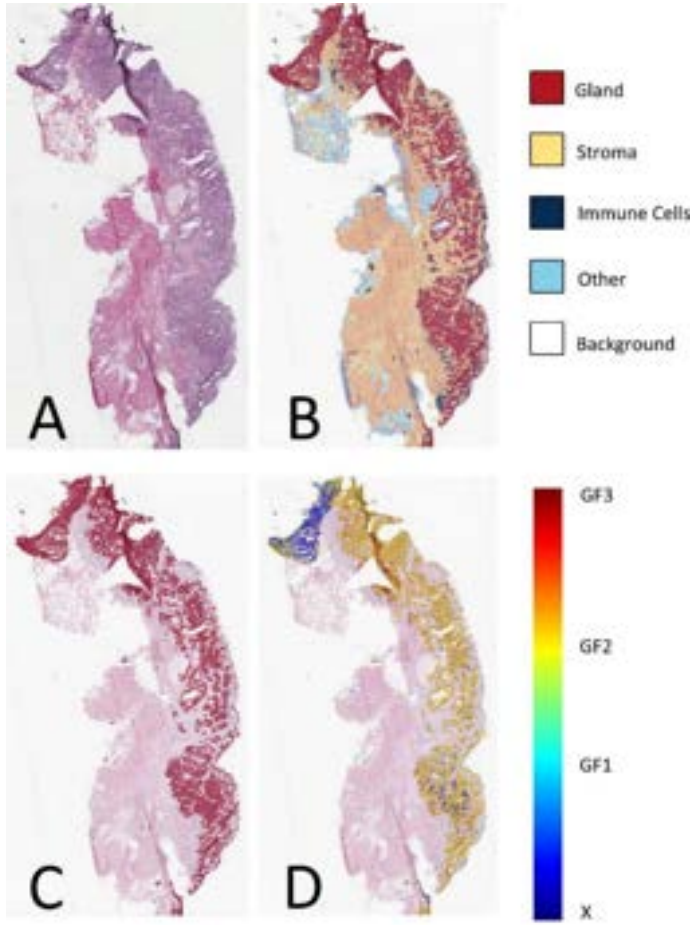
AI for Better Health Care

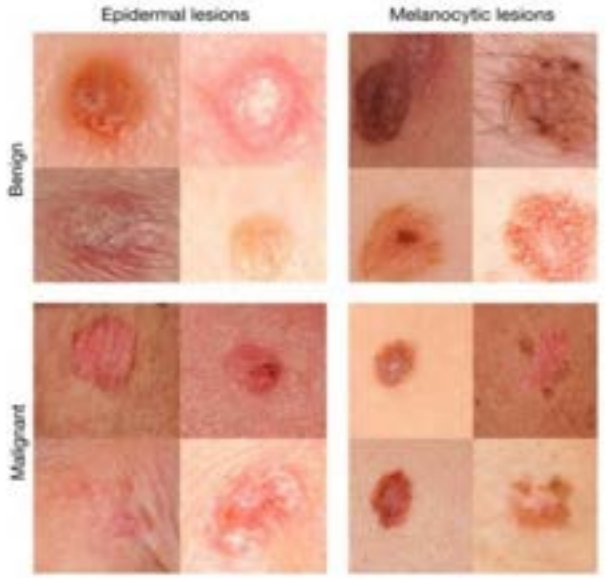


Source: nuance.com

AI for Better Processes

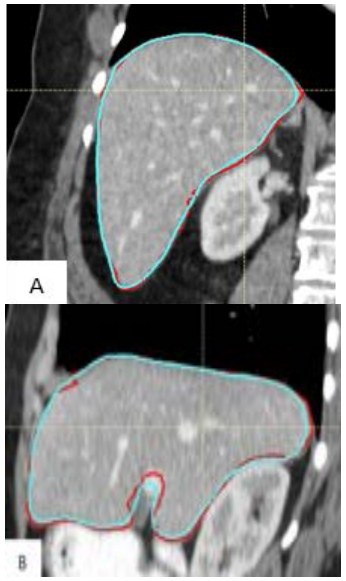




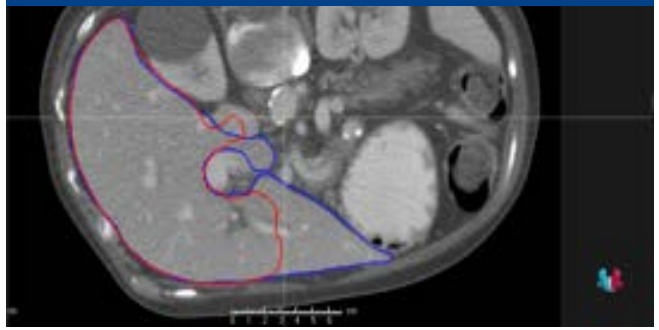


Artificial Intelligence is different than Human Intelligence

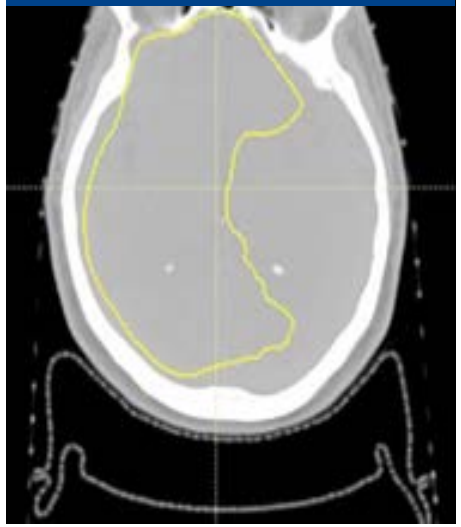
AI algorithms cannot be expected to perform at a higher level than their training data, but should deliver the same standard of performance consistently for data within the training space.

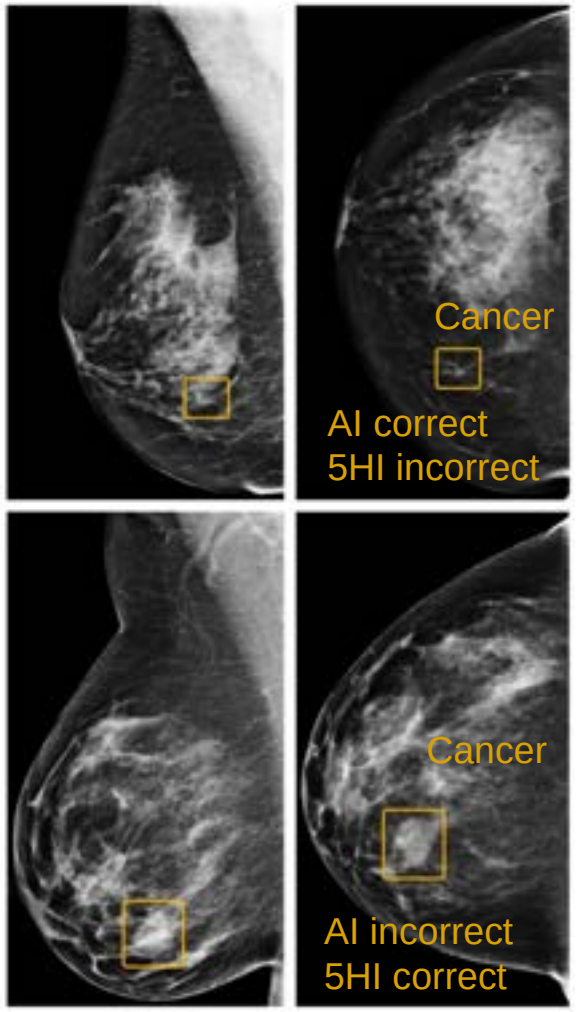


CT prone
All training data was supine



AI will find you a liver anywhere…





Images courtesy of MD Anderson / Brian M. Anderson Nature 2020, 577:89 | JASON, Artificial Intelligence for Health and Health Care, Dec 2017, JSR-17-Task-002

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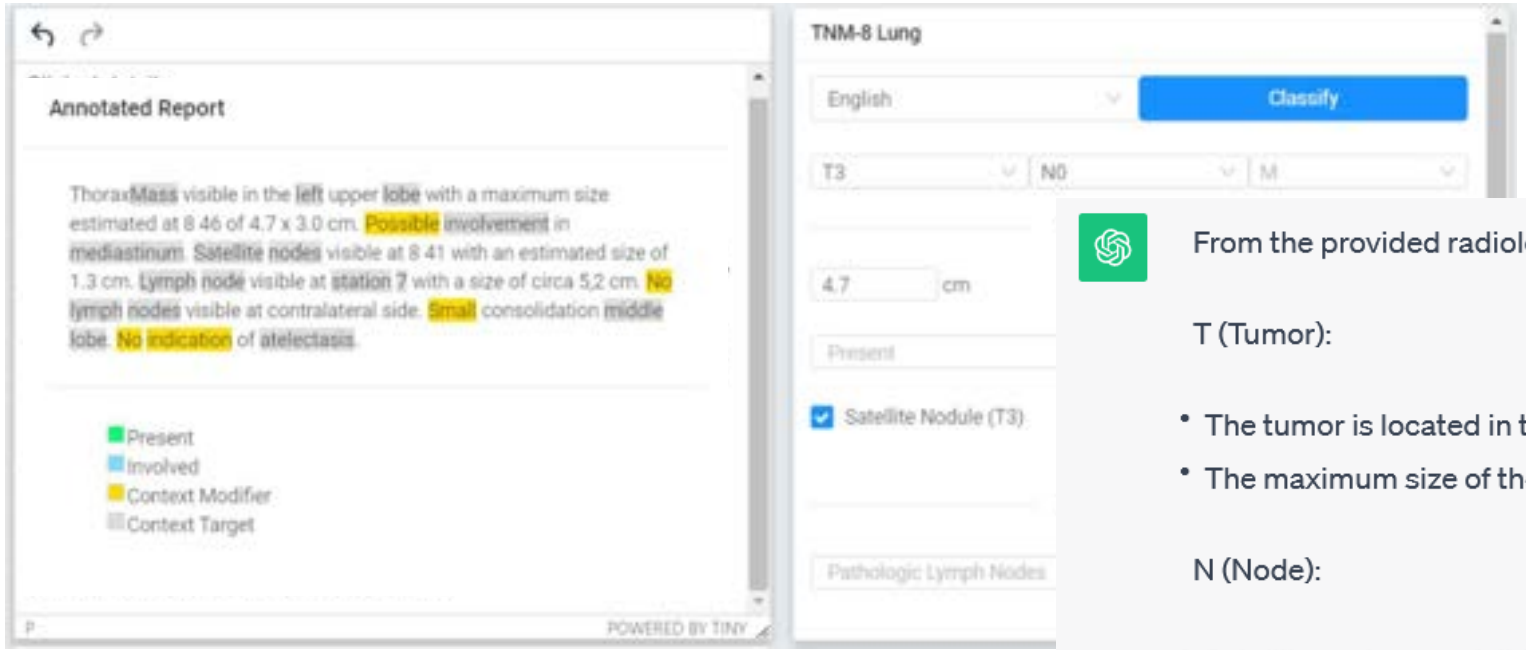
Hey, ChatGPT: can I trust you?

AN Please explain the toxic effects of lung radiotherapy used for STage III lung cancer

1. Fatigue
2. Radiation dermatitis
3. Radiation pneumonitis
4. Radiation esophagitis
5. Radiation-induced nausea and vomiting
6. Hair loss

1. Fatigue: Radiotherapy can induce severe fatigue and exhaustion in patients. This fatigue may persist throughout the treatment period and impact daily activities and overall quality of life.
2. Radiation dermatitis: The skin in the treated area can experience radiation-induced dermatitis, characterized by redness, dryness, and irritation. The skin may become sensitive and itchy. Proper skincare and the use of prescribed moisturizers can help alleviate these symptoms.
3. Radiation pneumonitis: Radiation therapy can cause inflammation in the lungs, leading to radiation pneumonitis. This condition manifests as a cough, shortness of breath, and chest discomfort. It typically occurs within a few months after treatment initiation and can be managed with anti-inflammatory medications.
4. Radiation esophagitis: The esophagus, the tube connecting the mouth to the stomach, may become inflamed and swollen due to radiation. This can result in painful swallowing, difficulty eating, and, in some cases, the development of ulcers. Medications and dietary modifications are often recommended to alleviate these symptoms.
5. Radiation-induced nausea and vomiting: Some individuals may experience nausea and vomiting as a result of radiation therapy. Antiemetic medications can be prescribed to control these side effects and minimize their impact.
6. Hair loss: In certain cases, localized hair loss may occur in the treated area, although it is important to note that hair loss specifically on the head is not a common side effect of lung radiotherapy.

Better – Processes – NLP



From the provided radiology report, we can extract the T and N stages as follows:

T (Tumor):

- The tumor is located in the left upper lobe of the thorax.
- The maximum size of the tumor is estimated at 4.7 × 3.0 cm.

N (Node):

- Satellite nodes are visible at station 8-41 with an estimated size of 1.3 cm.
- A lymph node is visible at station 7 with a size of approximately 5.2 cm.
- No lymph nodes are visible on the contralateral side.

Based on the information in the report, the T stage is T2 (since the tumor size exceeds 3 cm but is 5 cm or less), and the N stage would be N2 (due to the presence of lymph nodes in station 7 and satellite nodes). However, the complete TNM stage would also depend on

NEWS

Texas professor flunked whole class after ChatGPT it wrote their papers

By Natalie O'Neill

May 18, 2023 | 3:05pm | Updated

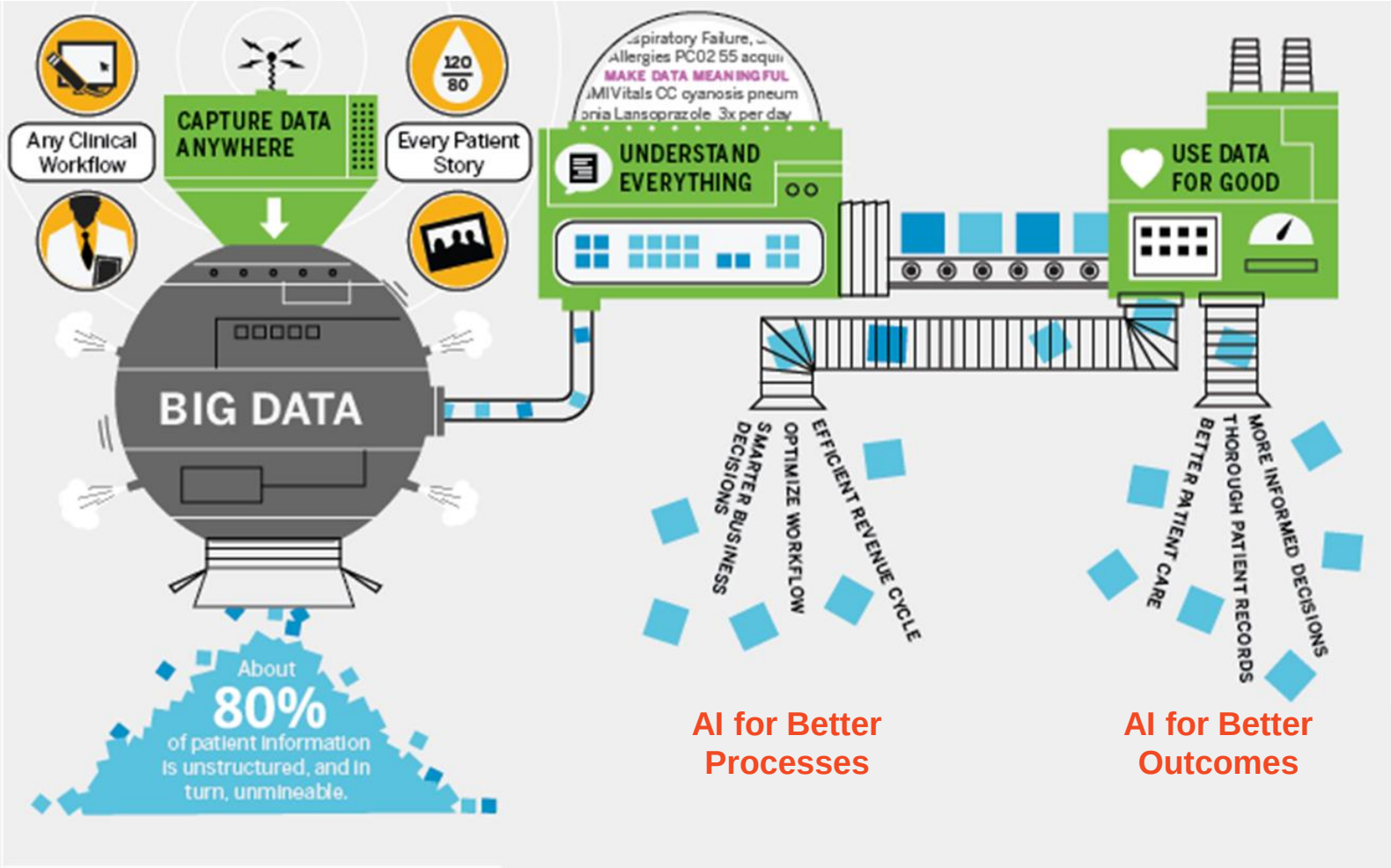
Do AIs need to be perfect?

AI algorithms cannot be expected to perform at a higher level than their training data, but should deliver the same standard of performance consistently for data within the training space.

JASON, Artificial Intelligence for Health and Health Care, Dec 2017, JSR-17-Ta

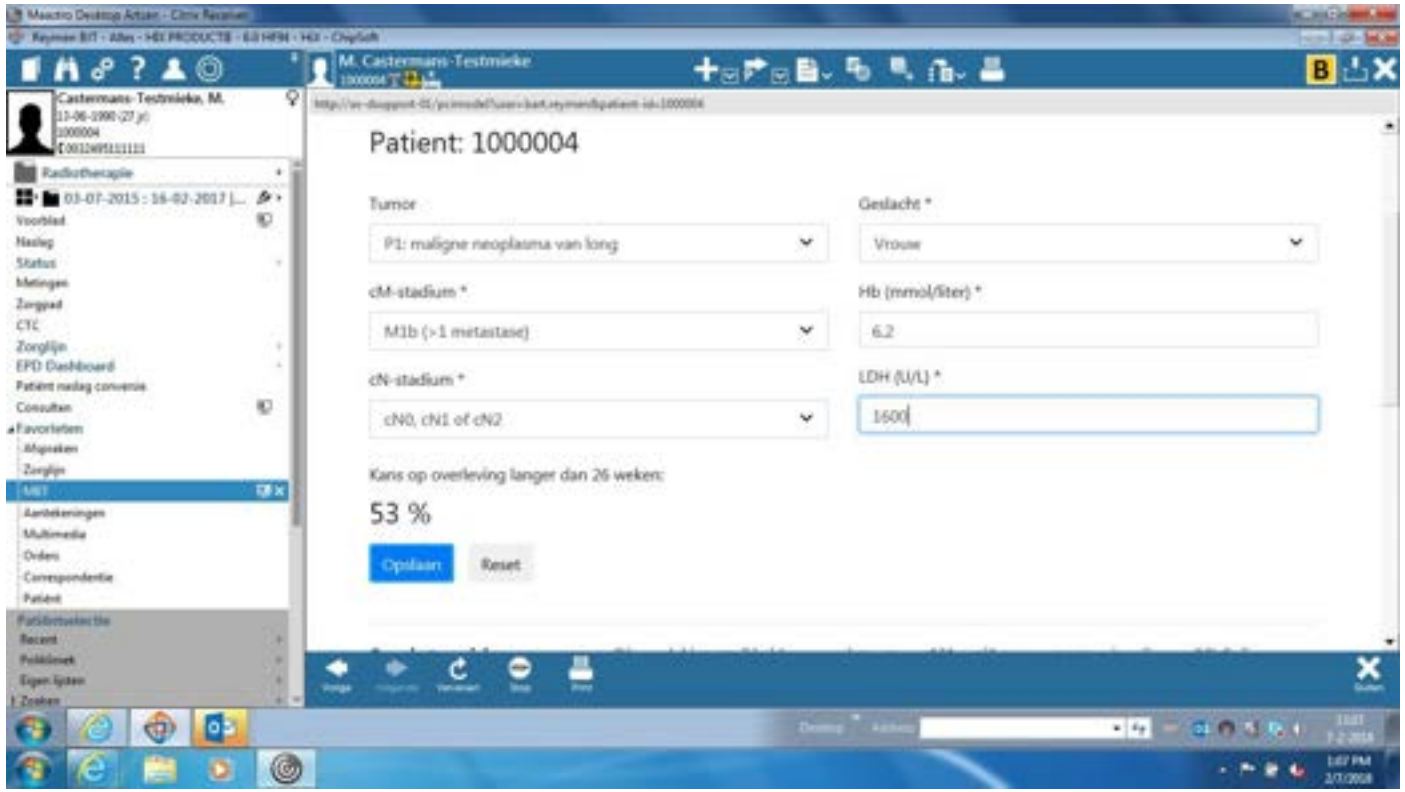
Trust in model vs own expertise

AI for Better Health Care



Source: nuance.com

Small Cell Lung Cancer – Shared Decision Making – Grey Area Guideline



AGE

Short survival – no PCI?

Experience patient: Decisional Conflict, Control Preference, SDM

Experience MD, SDM

Cost Effectiveness; Care path

Better Outcomes – Prediabetes

Apollo HOSPITALS

PREDIABETES RISK SCORE

NAME: SAIRAM	AGE: 22	LOCATION: PALAKOL
UHID: 123456789	GENDER: MALE	DATE OF REPORT: 10-11-2021

PATIENT RISK SCORE

Risk	Score
Low Risk	80

INFORMED CONSENT: YES

Height	147	Weight	58
BMI	26.84	Diet	Non-Veg
Alcohol	No	Waist Circumference	34
Change in Body Weight	Same	Physical Activity	Mild
Family History of Diabetes	Yes	Dyslipidemia	No
Hypertension	Yes	Symptoms	No
Past Medical History	No		

RECOMMENDED PROTOCOL

Activity

Increase physical activity. Should aim or 30 minutes of moderately intense exercise (such as a brisk walk) most days of the week, for a minimum of 150 minutes (2.5 hours) of total physical activity per week.

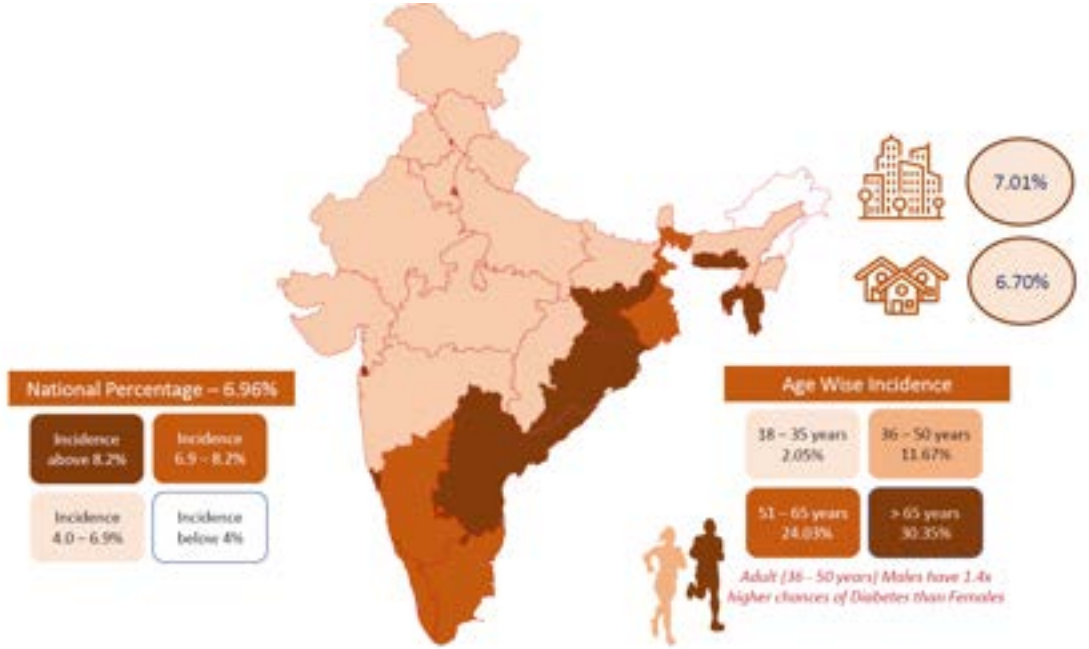
Nutrition

Low Carbohydrate, Low Fat diet

Referral to consultant

Not Required

AUC~0.8



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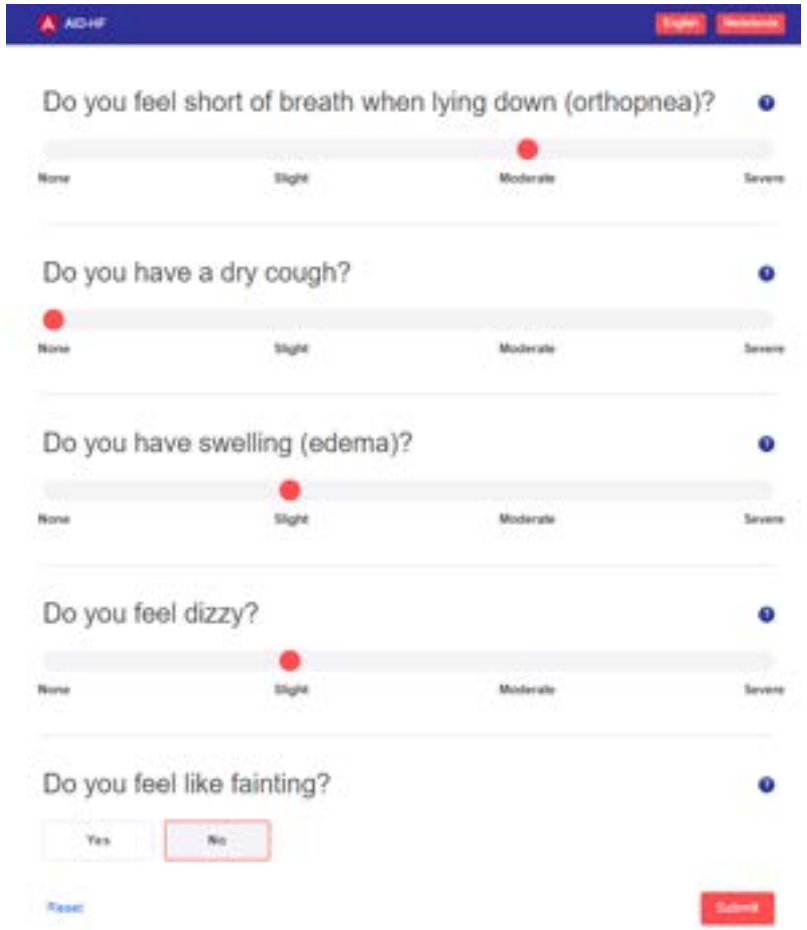
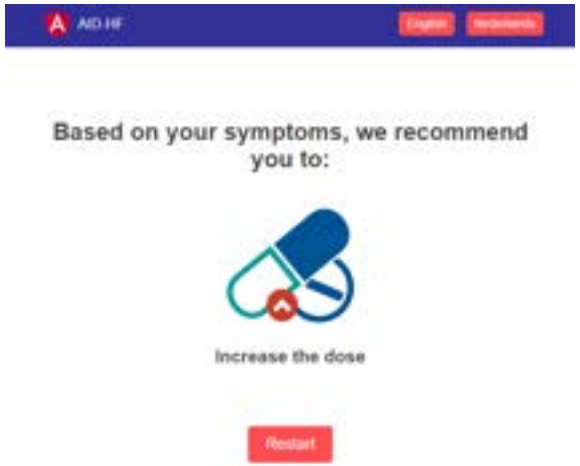
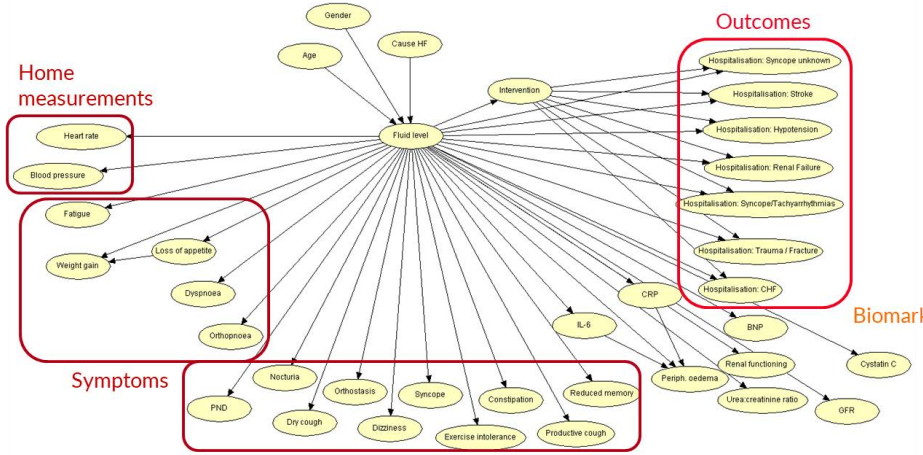
Better Outcomes – Self-medication in Chronic Heart Failure







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Better Outcomes – Model Based Indication

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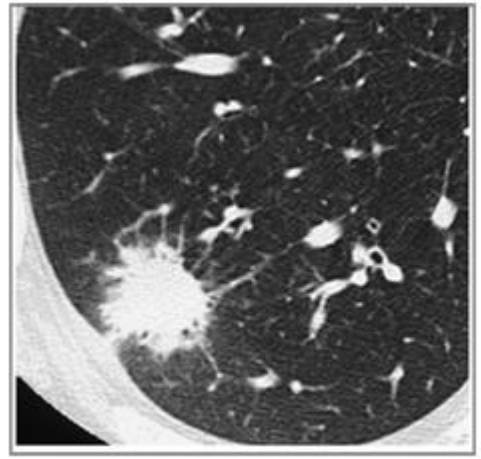
Some things to get you thinking

Typical Data Quality challenges

- Data are unstructured
- Data are not understandable
- Data are missing
- Data are incorrect
- Data are contradicting
- Data are biased
- Data are biased missing

声门下区



T4N0M0 Stage IV patient

Patient weighing 1000kg

- Garbage in – Garbage out?

Grade 3+ toxicities

Who is this?

Pressure-Volume Loops in Cardiac Surgery

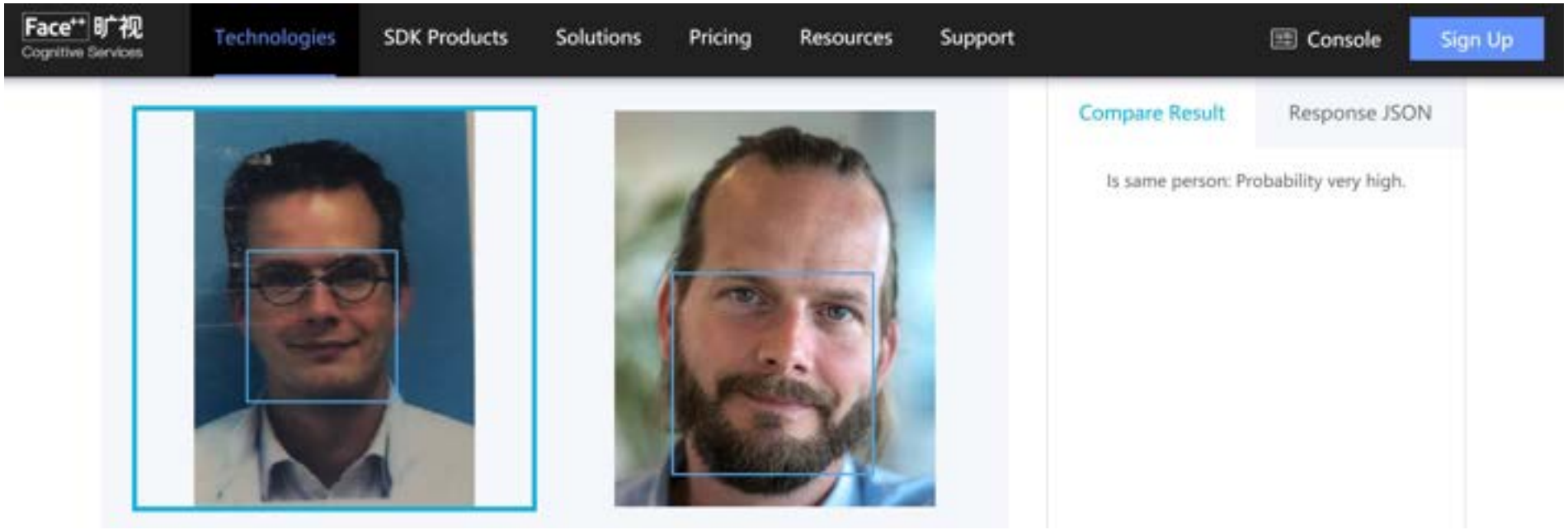
Proefschrift

ter verkrijging van de graad van doctor
aan de Universiteit Maastricht,
op gezag van de Rector Magnificus,
Prof.dr. A.C. Nieuwenhuijzen Kruseman,
volgens het besluit van het College van Decanen,
in het openbaar te verdedigen,
op vrijdag 12 september 2003 om 14:00 uur

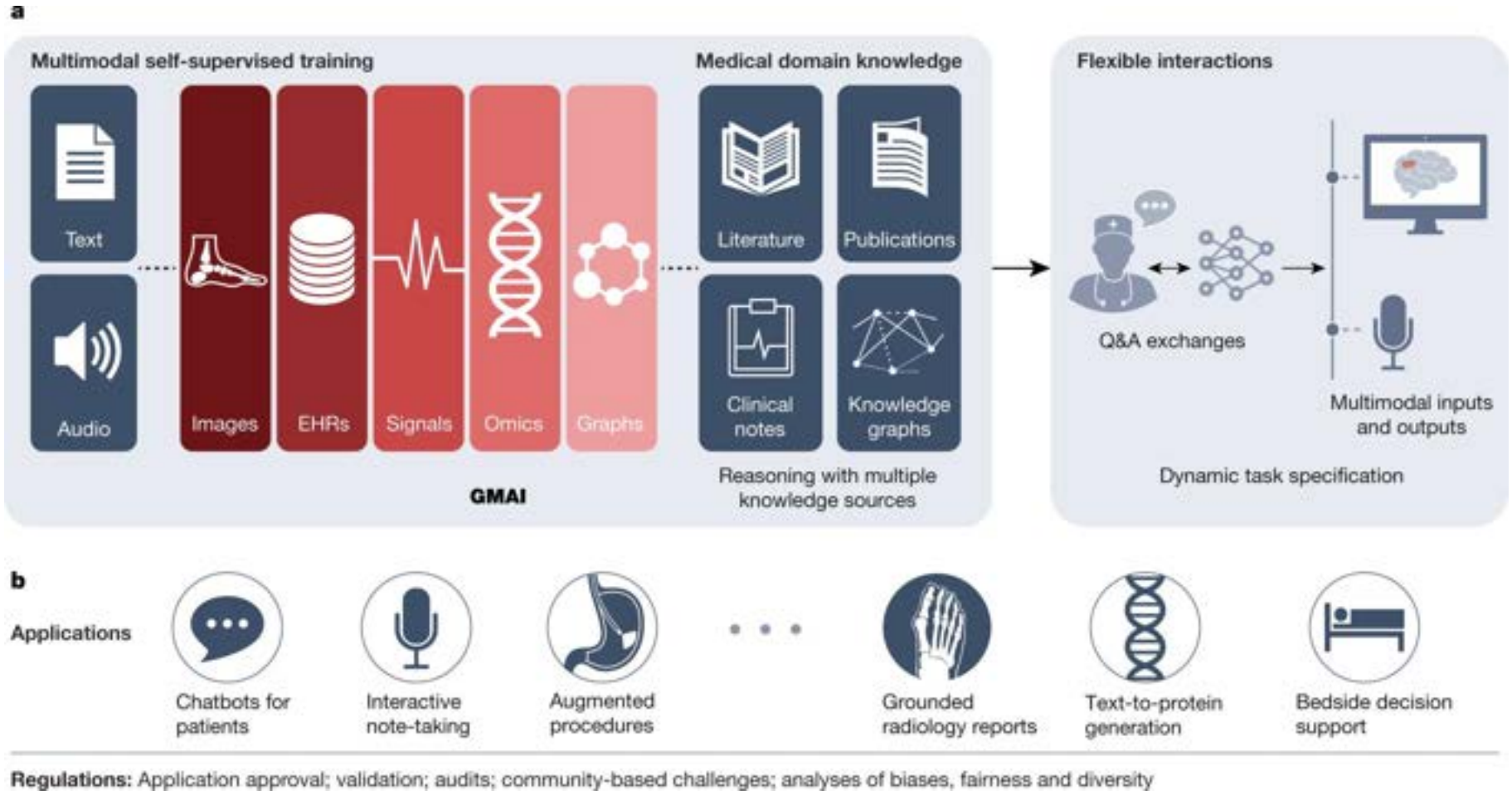
door

André Dekker

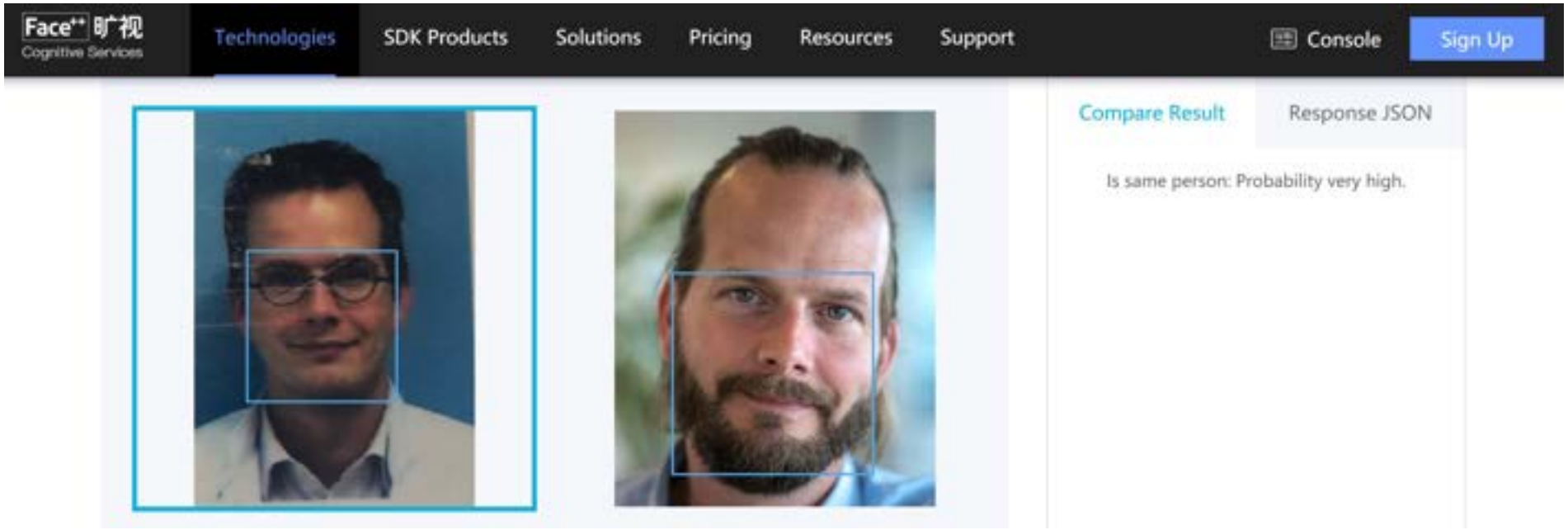
Good enough for AI



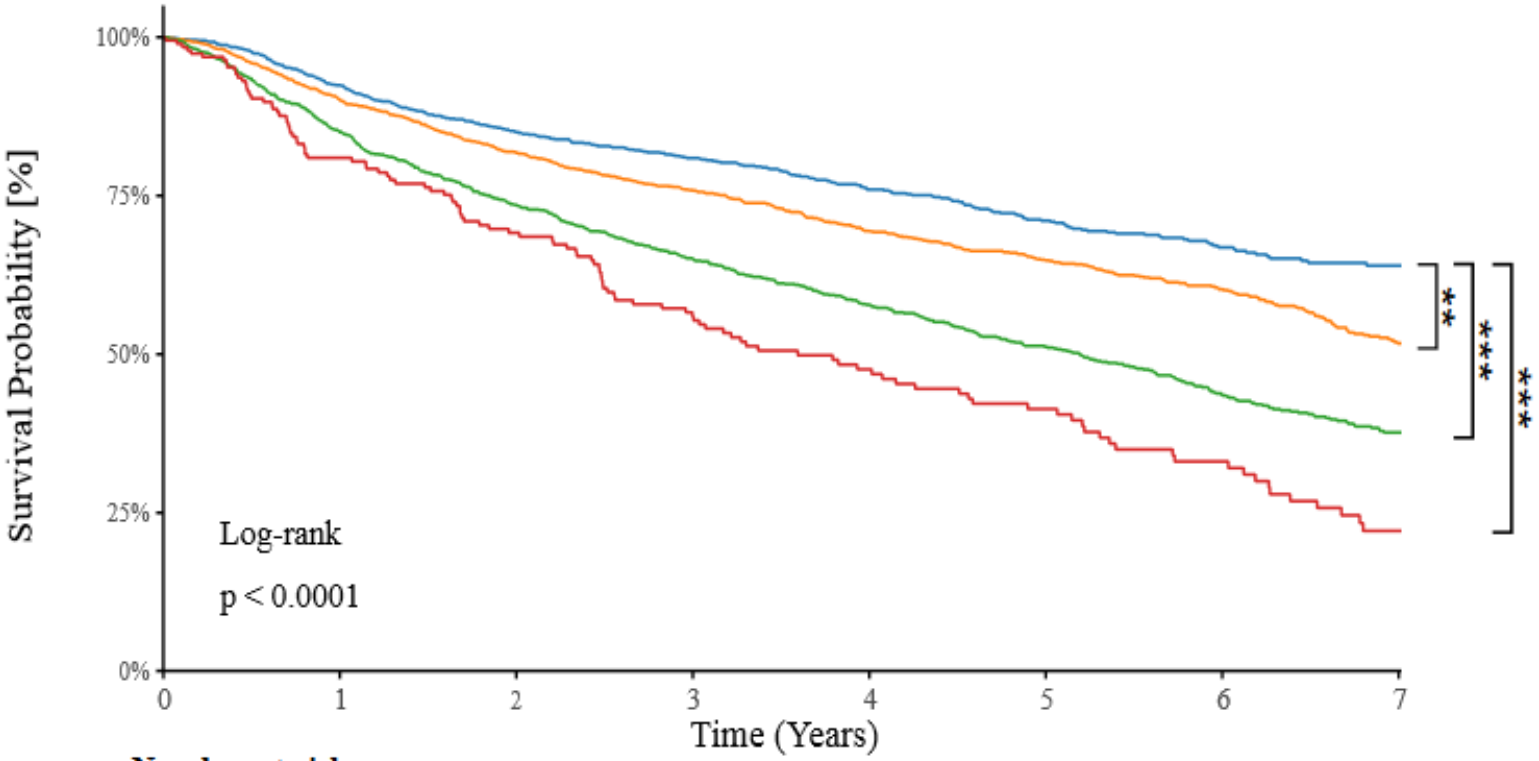
~~Garbage in – Garbage out~~

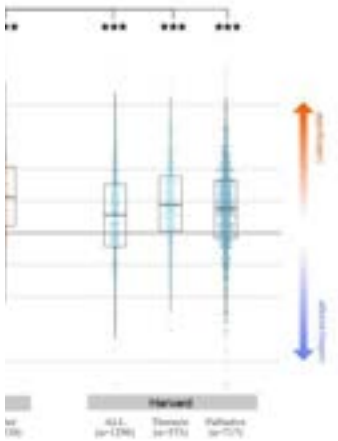


Good enough for AI



FaceAge





Number at risk

FaceAge ≤ 65	1385	1067	861	700	536	409	250	128
65 < FaceAge ≤ 75	2035	1565	1300	1062	815	634	419	228
75 < FaceAge ≤ 85	1292	983	791	628	487	377	259	153
FaceAge > 85	194	143	114	88	64	49	32	17

Zalay et al. medRxiv. 2023 Sep 12;2023.09.12.23295132.

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Key messages

- We need AI for better processes and better outcomes in health care

- Trends
  - FAIR Federated Data Infra
  - Deep learning
  - Companion AI for better indications & shared decision making

- Cautions
  - Bias | Causality | Culture | Quality | Ethics

- What is responsible and what is compliant?
  - Irresponsible is not to share data and not to develop AI
  - Compliance in terms of privacy is clear, other ELSI less so

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Thank you for your attention