Olivier Cussenot

Préface Denis Kessler

Medical Decision-Making in the age of Artificial Intelligence

SCOR
The Art & Science of Risk

Webinar 2 March 2023

OUTLINE

1-Introduction to decision-making in medicine
2-Human intelligence & decision-making
3-Algorithmic medicine & decision-making
4-Conclusion

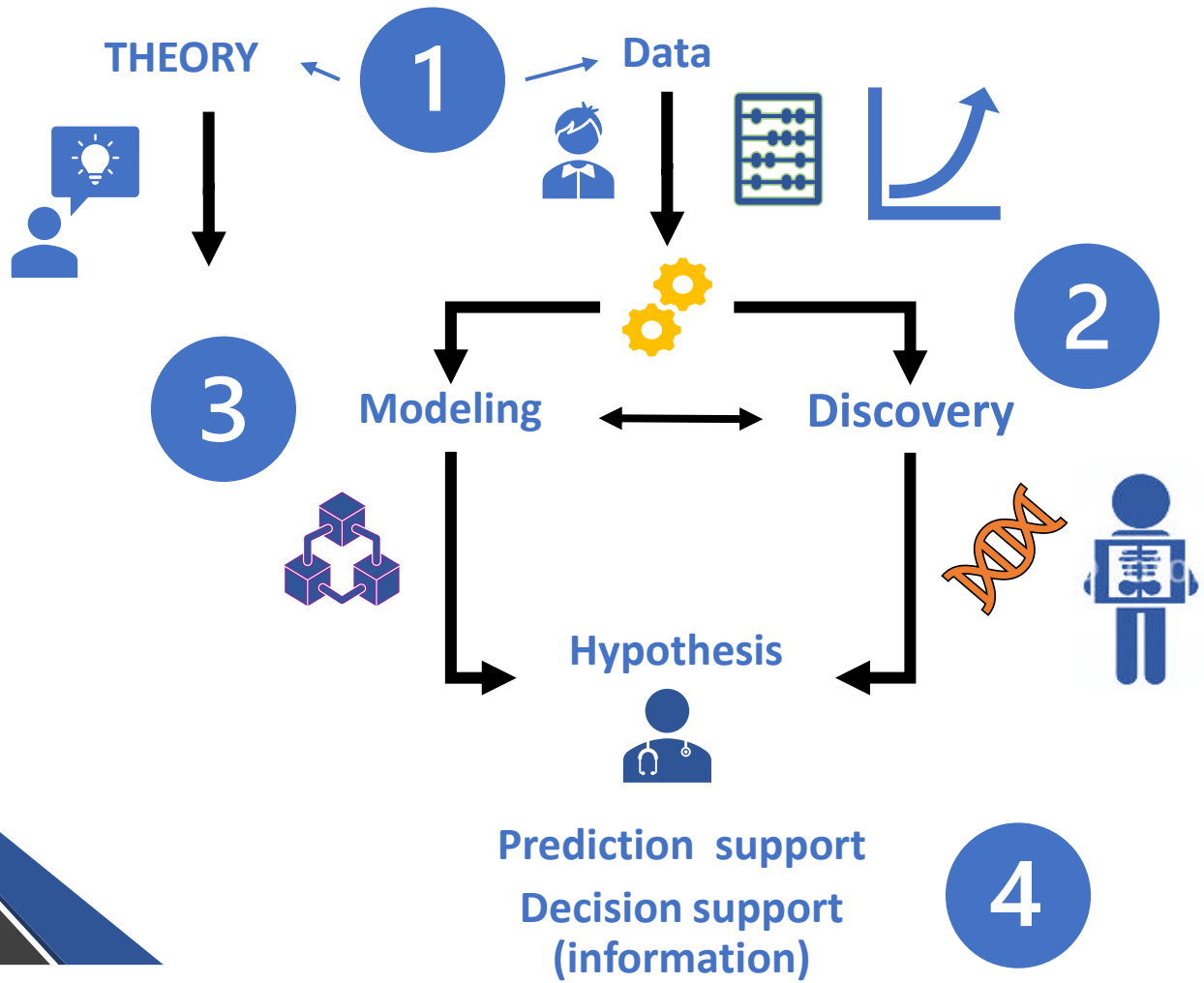
1-Introduction to decision-making in medicine

Purposes & Context

Actors & audiences

Predictive & Decision-making in Medicine

The experience of the team



Key issues *according to J. Pearl*

1 **What can I deduce by observing this?**
(e.g.: What does this sign tell me about this disease?)

Prediction

2 **What happens if I do this?**
(e.g. will this treatment be effective?)

Decision

Regret

3 **What would have happened if I had done that?**
(e.g. is the therapeutic hazard observed due to my treatment?)

❖**Prediction:**

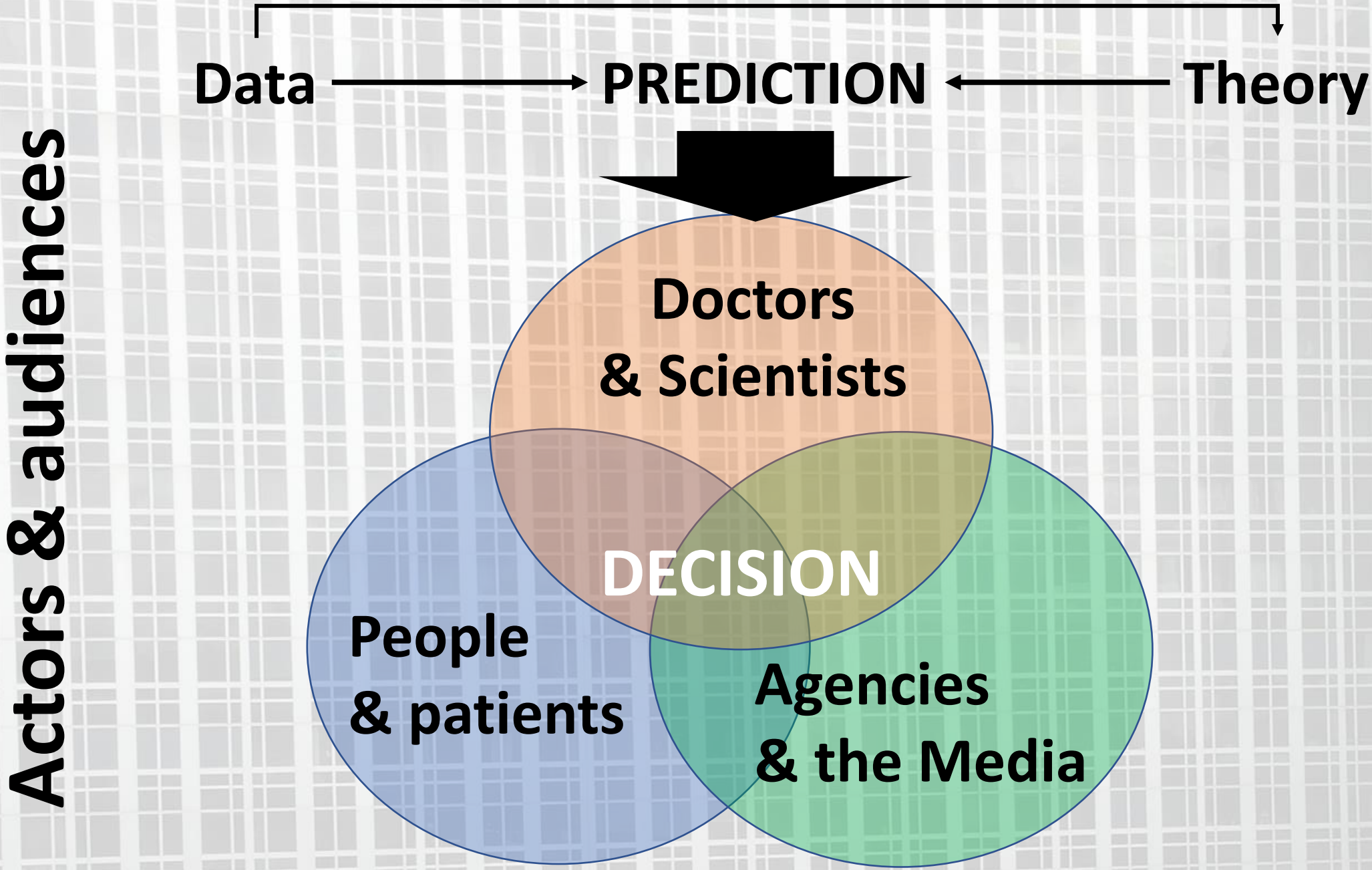
Announce an event in advance by calculation or by reasoning

❖**Decision:**

Choosing between several solutions that may solve a problem

❖**Regret:**

A feeling of sadness about a mistake that you have made, and a wish that it could have been different and better


Data
PREDICTION
Theory
Actors & audiences
Doctors
& Scientists
DECISION
People
& patients
Agencies
& the Media

2-Human intelligence & decision-making

Evidence based Medicine

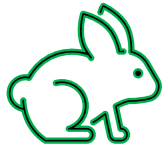
- Overview & current drift

Limitations and errors

- Cognitive illusion assessment
- Deciphering errors in prostate cancer policies

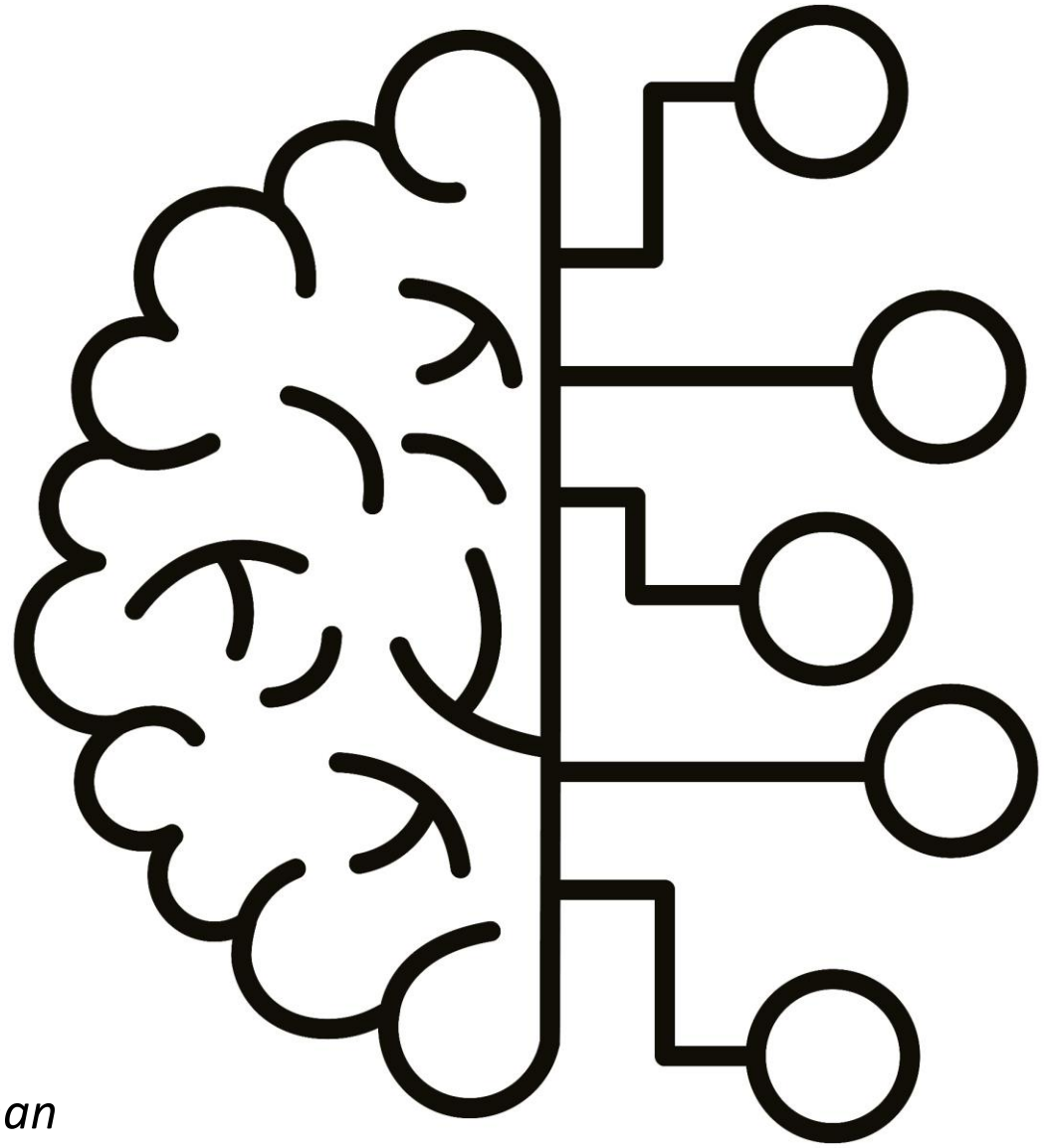
Thinking and Decision-Making

SYSTEME 1
Instinct & Intuition

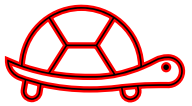


95%

According to D. Kahneman



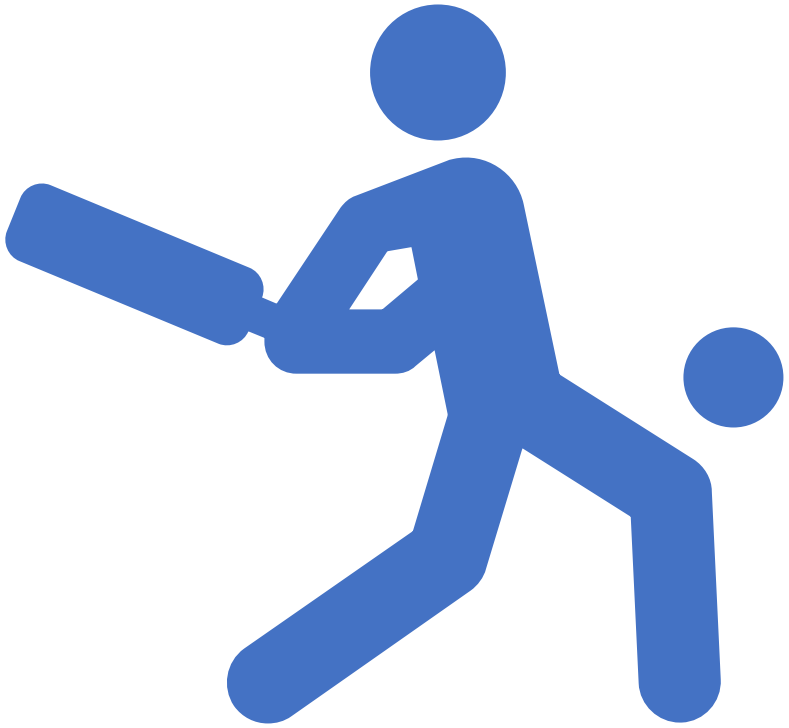
SYSTEME 2
Rational & Logic

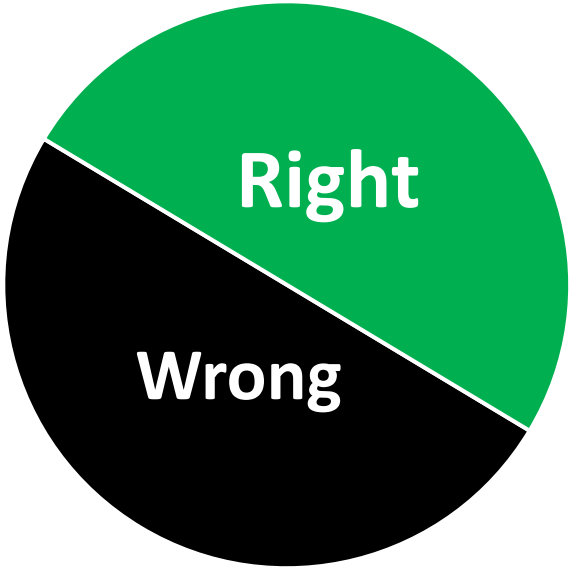


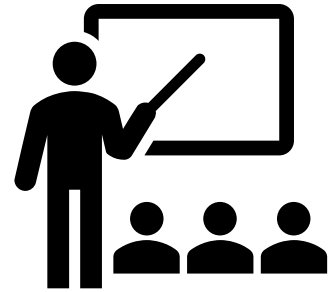
5%

Bat + ball = 10$

Bat costs 9$ more than the ball



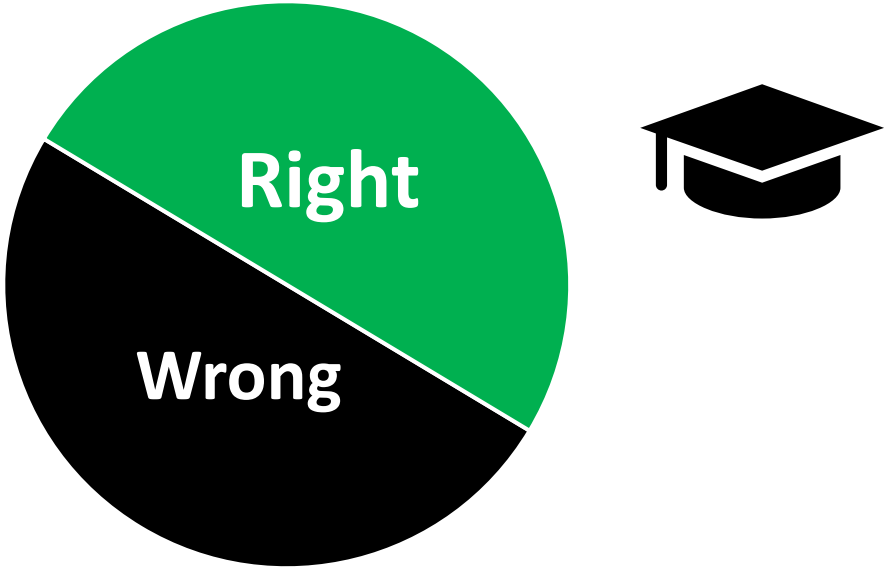




How much does the ball cost ?

Bat + ball = 10$

Bat costs 9$ more than the ball

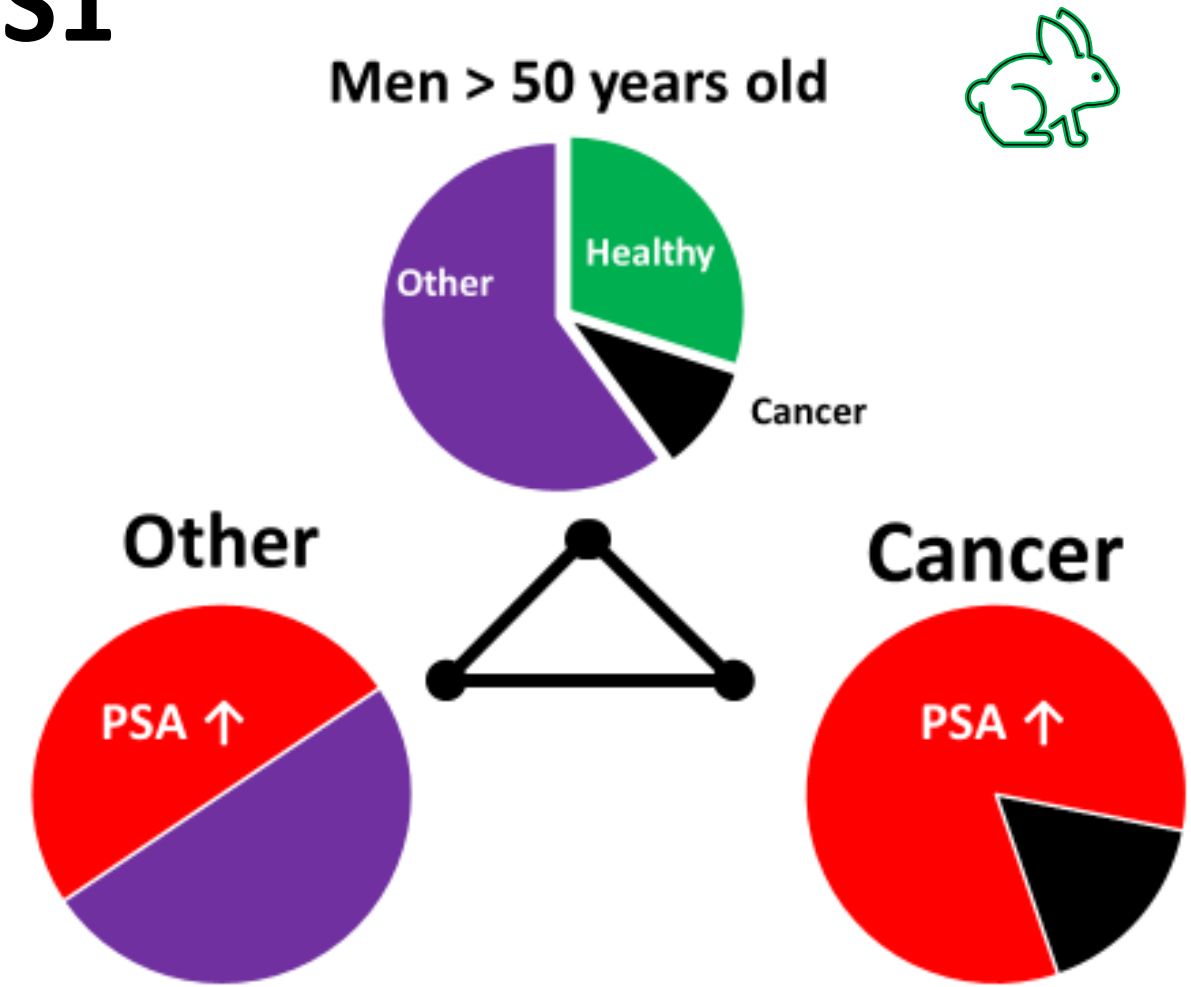


How much does the ball cost ?

Prostate cancer as guiding thread

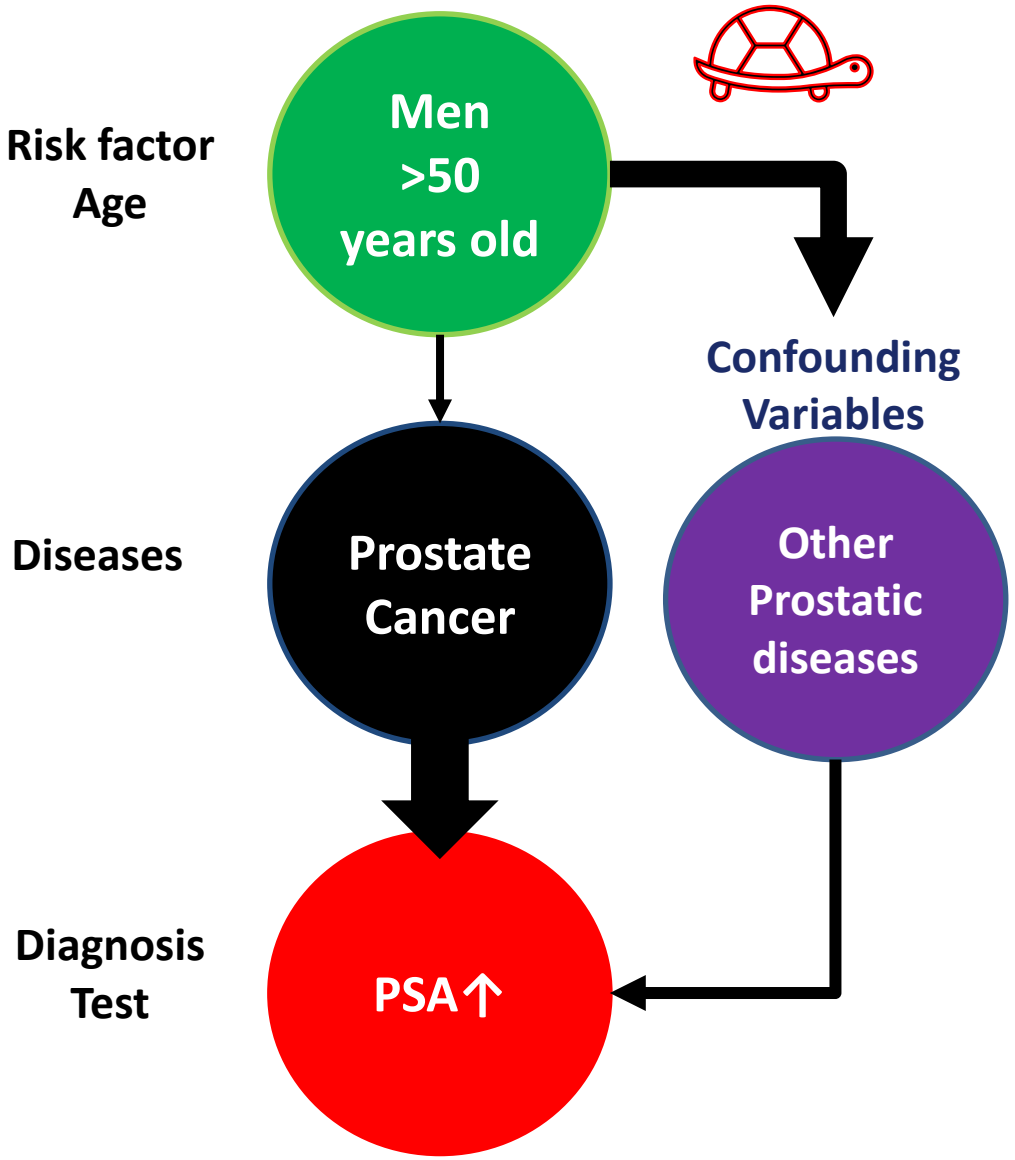
Association - Intuition

S1



Causality - Calculation

S2



Typology of Reasoning

S1

Paleo-reasoning (Fast Thinking)

Associative

Symmetrical

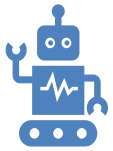
S2

Neo-reasoning (Slow Thinking)

Logic

Asymmetric

Causal



→Machine learning

← Research

Theory
Model
Rules

Clinical practice →

Data
clinical cases

→ Symbolic AI

Conclusion
Hypothesis

Logical reasoning: Asymmetric (Causal)

Aristotle (384-322 BC JC)

Syllogism

Men → mortal

→ X is a man

→ X is mortal

Theory

Cancer → PSA

Observation

Cancer

Conclusion

Obs → PSA

Deduction

If & If → Then

Cancer → PSA↑

→ X has a Cancer

→ X has PSA↑

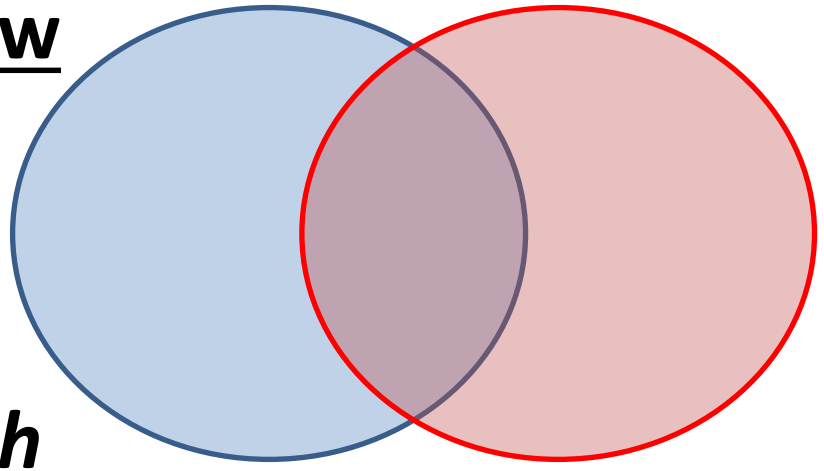
→ **Symbolic AI**

Evidence Based Medicine

The aim of EBM is to integrate the best available scientific information to guide decision-making about clinical management

Scientific Theory & Law

Physics
Biology
Translational research



Clinical trials

Statistics

The foundations of the Evidence Based Medicine

Reasoning in Clinical Research → EBM

Individual profiles → General law / theory

Establishing a rule

Theory

Cancer → PSA

Induction

Observation

Cancers

Research

Conclusion

Obs → PSA

David Hume (1711-1776)

Hypothesis H0 to be rejected?
Likely hypothesis?

Yes / No
Universal decision

↑

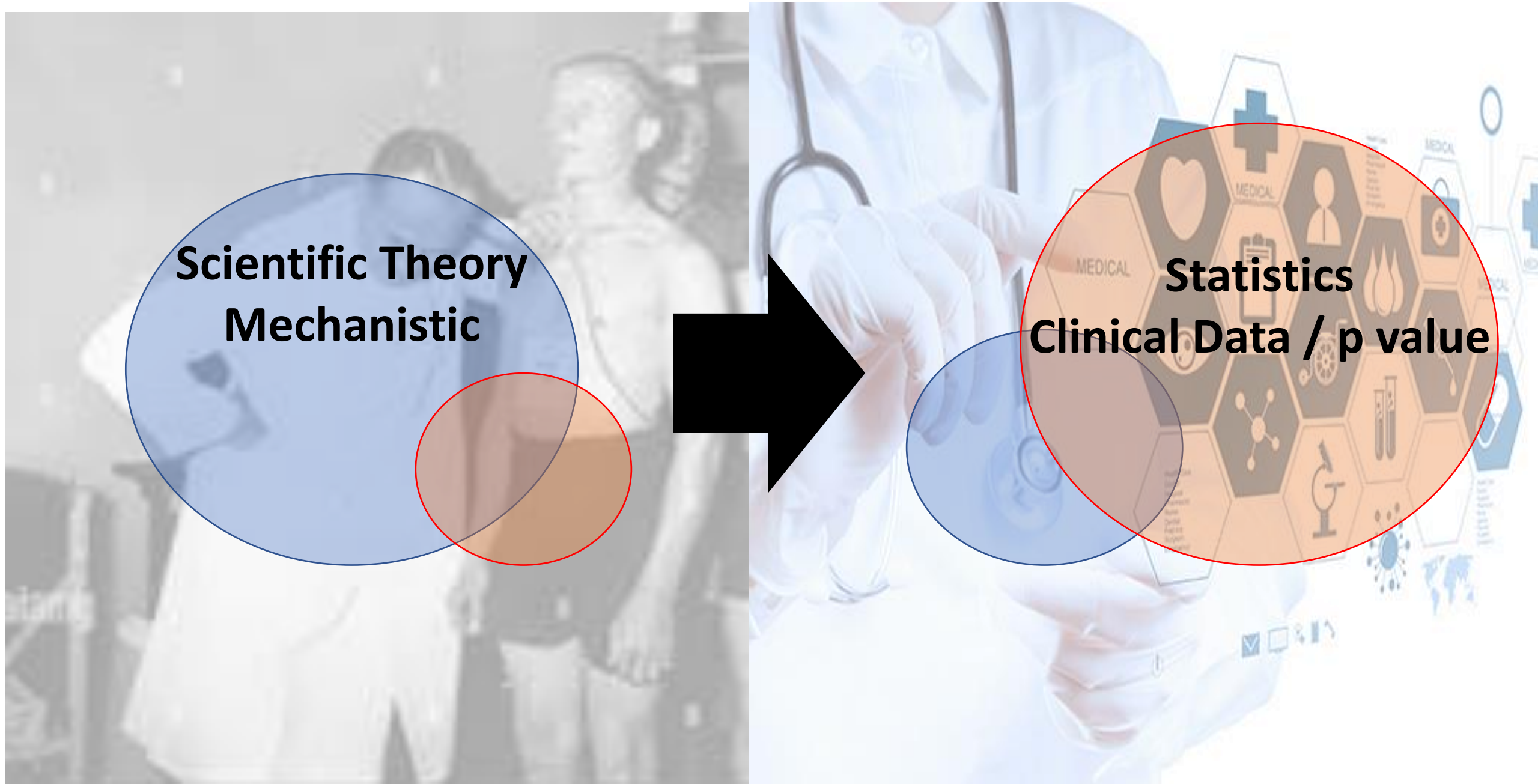
Algorithm

↑

Data ∞

Decision problem

Evidence Based Medicine drift



Clinical research

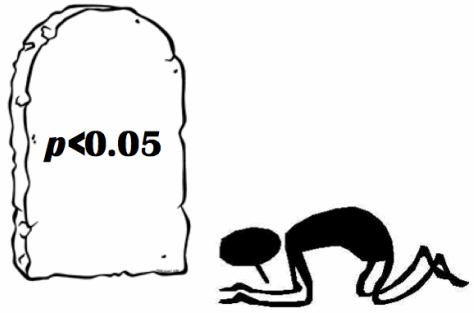
Real life

Databases

Selection bias
Interactions

Inference
by Induction

Studies
Randomized



Randomized trial ≠ scientific relevance

Parachute use to prevent death and major trauma related to gravitational challenge: systematic review of randomised controlled trials

BMJ december 2003 Vol 327

Gordon C S Smith, Jill P Pell

Abstract

Objectives To determine whether parachutes are effective in preventing major trauma related to gravitational challenge.

Design Systematic review of randomised controlled trials.

Data sources: Medline, Web of Science, Embase, and the Cochrane Library databases; appropriate internet sites and citation lists.

Study selection: Studies showing the effects of using a parachute during free fall.

Main outcome measure Death or major trauma, defined as an injury severity score > 15.

Results We were unable to identify any randomised controlled trials of parachute intervention.

Conclusions As with many interventions intended to prevent ill health, the effectiveness of parachutes has not been subjected to rigorous evaluation by using randomised controlled trials. Advocates of evidence based medicine have criticised the adoption of interventions evaluated by using only observational data. We think that everyone might benefit if the most radical protagonists of evidence based medicine

accepted intervention was a fabric device, secured by strings to a harness worn by the participant and released (either automatically or manually) during free fall with the purpose of limiting the rate of descent. We excluded studies that had no control group.

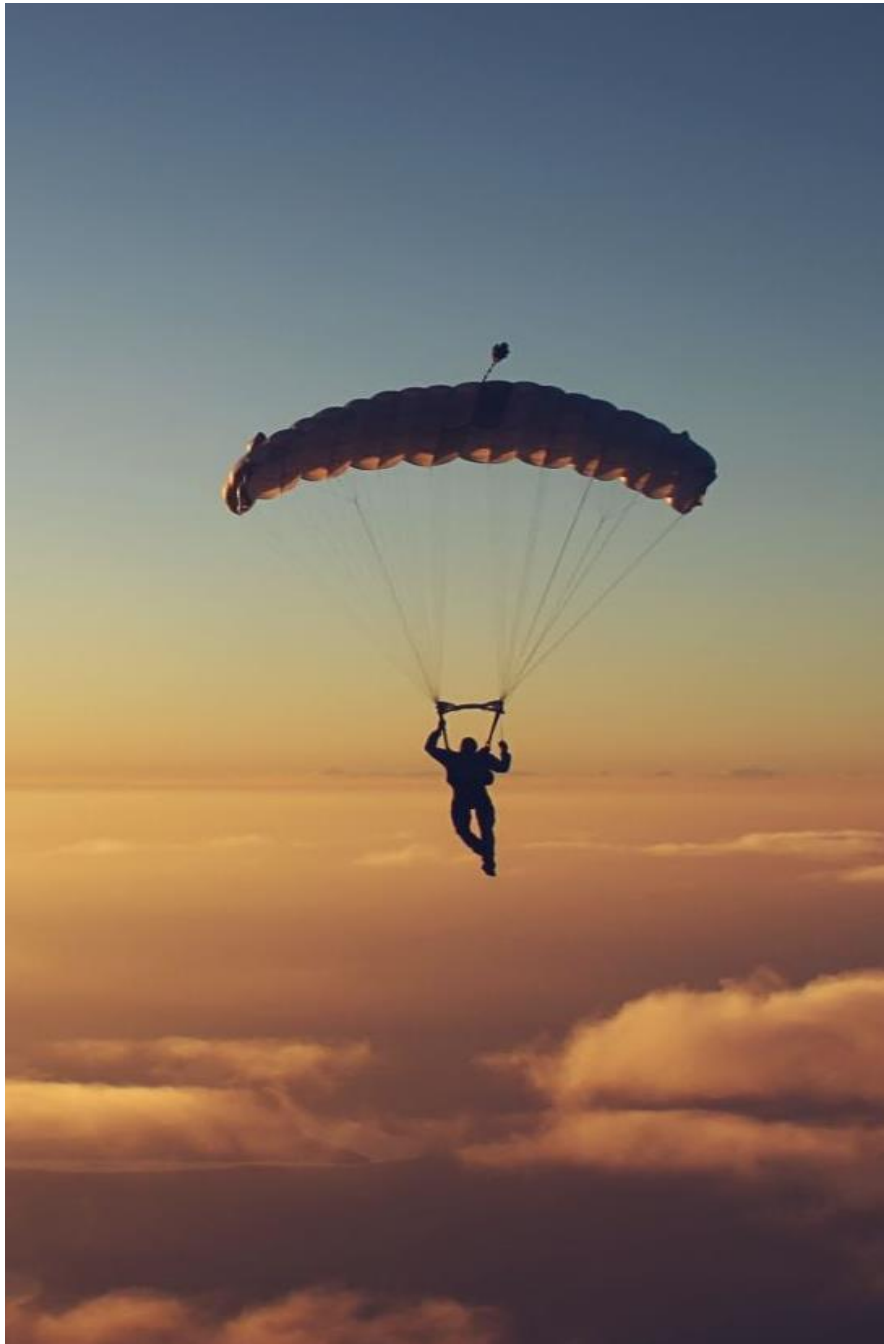
Definition of outcomes

The major outcomes studied were death or major trauma, defined as an injury severity score greater than 15.[6]

Meta-analysis

Our statistical apprach was to assess outcomes in parachute and control groups by odds ratios and quantified the precision of estimates by 95% confidence intervals. We chose the Mantel-Haenszel test to assess heterogeneity, and sensitivity and subgroup analyses and fixed effects weighted regression techniques to explore causes of heterogeneity. We selected a funnel plot to assess publication bias visually and Egger's and Begg's tests to test it quantitatively. Stata software, version 7.0, was the tool for all statistical analyses.

Results



p value <5% ≠ Scientific Reality

Empirical Article

aps ASSOCIATION FOR PSYCHOLOGICAL SCIENCE

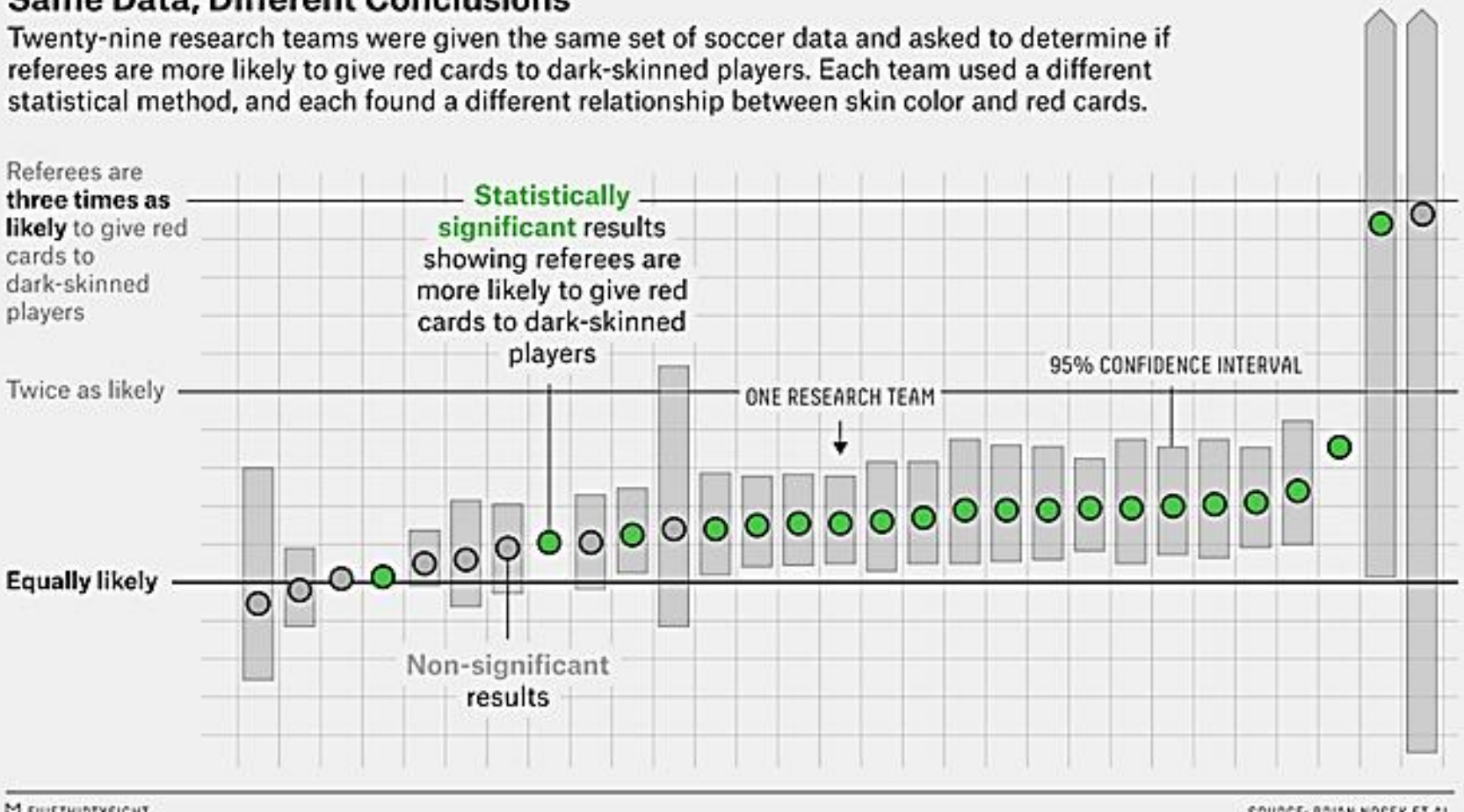
Many Analysts, One Data Set: Making Transparent How Variations in Analytic Choices Affect Results

Advances in Methods and Practices in Psychological Science
2018, Vol. 1(3) 337–356

DOI: 10.1177/2515245917747646

Same Data, Different Conclusions

Twenty-nine research teams were given the same set of soccer data and asked to determine if referees are more likely to give red cards to dark-skinned players. Each team used a different statistical method, and each found a different relationship between skin color and red cards.



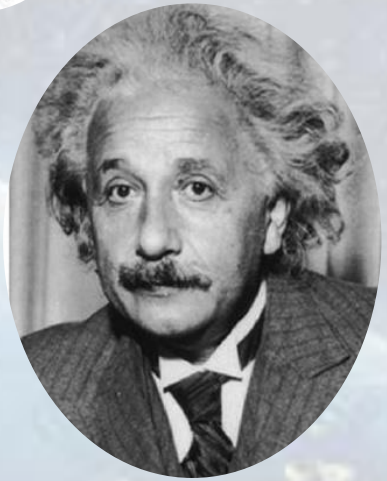
Clinical research

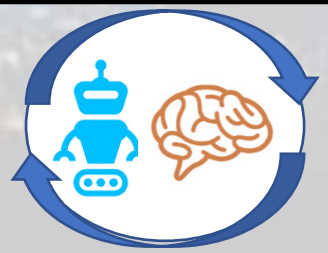
Geocentrism

Heliocentrism

p-Value <0.05 ?

« Evidence based Medicine »





Learning

CLINICAL INTUITION

Inference

by Abduction

Clinical reasoning

General law / theory → individual case

Establishing a diagnosis

Theory

Cancer → PSA

Observation

Cancer

Abduction

Conclusion

Obs → PSA

Charles S. Peirce (1839-1914) Semeiology

Cognitive illusions: the limits of Human Intelligence

Cognitive illusions & Unconscious bias

Perception
Deduction
Calculation

Inference
Observational

Just the reality

Check all information without a subjective lecture

you have 10 seconds to count the number of «F»

FINISHED FILES ARE THE RESULT OF YEARS OF SCIENTIFIC STUDY COMBINED WITH THE EXPERIENCE OF YEARS

The number of «F»

2 ☐
3 ☐
4 ☐
5 ☐
6 ☑

FINISHED FILES ARE
THE RESULT OF YEARS OF SCIENTIFIC STUDY
COMBINED WITH THE EXPERIENCE OF YEARS

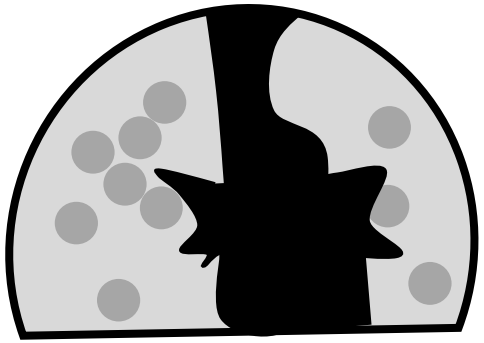
Published in final edited form as:
Psychol Sci. 2013 September ; 24(9): 1848–1853. doi:10.1177/0956797613479386.

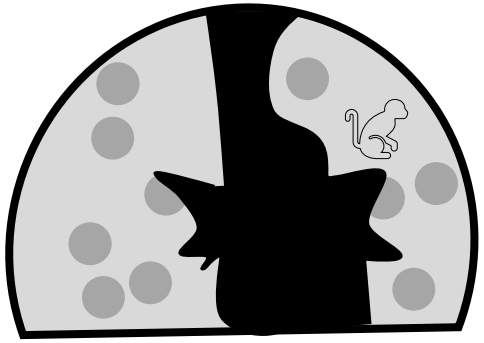
"The invisible gorilla strikes again: Sustained inattentional blindness in expert observers"

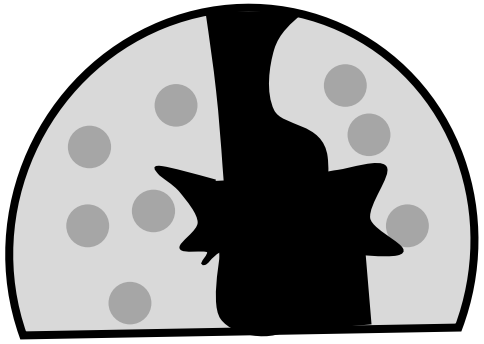
Trafton Drew, **Melissa L. H. Vo**, and **Jeremy M. Wolfe**
Trafton Drew: TraftonDrew@gmail.com

Abstract

We like to think that we would notice the occurrence of an unexpected yet salient event in our world. However, we know that people often miss such events if they are engaged in a different task, a phenomenon known as "inattentional blindness." Still, these demonstrations typically involve naïve observers engaged in an unfamiliar task. What about expert searchers who have spent years honing their ability to detect small abnormalities in specific types of image? We asked 24 radiologists to perform a familiar lung nodule detection task. A gorilla, 48 times larger than the average nodule, was inserted in the last case. 83% of radiologists did not see the gorilla. Eye-tracking revealed that the majority of the those who missed the gorilla looked directly at the location of the gorilla. Even expert searchers, operating in their domain of expertise, are vulnerable to inattentional blindness.







In an up-to $200M Acquisition by Nanox, Zebra Medical Vision Brings Its AI to Reimagine Radiology Globally

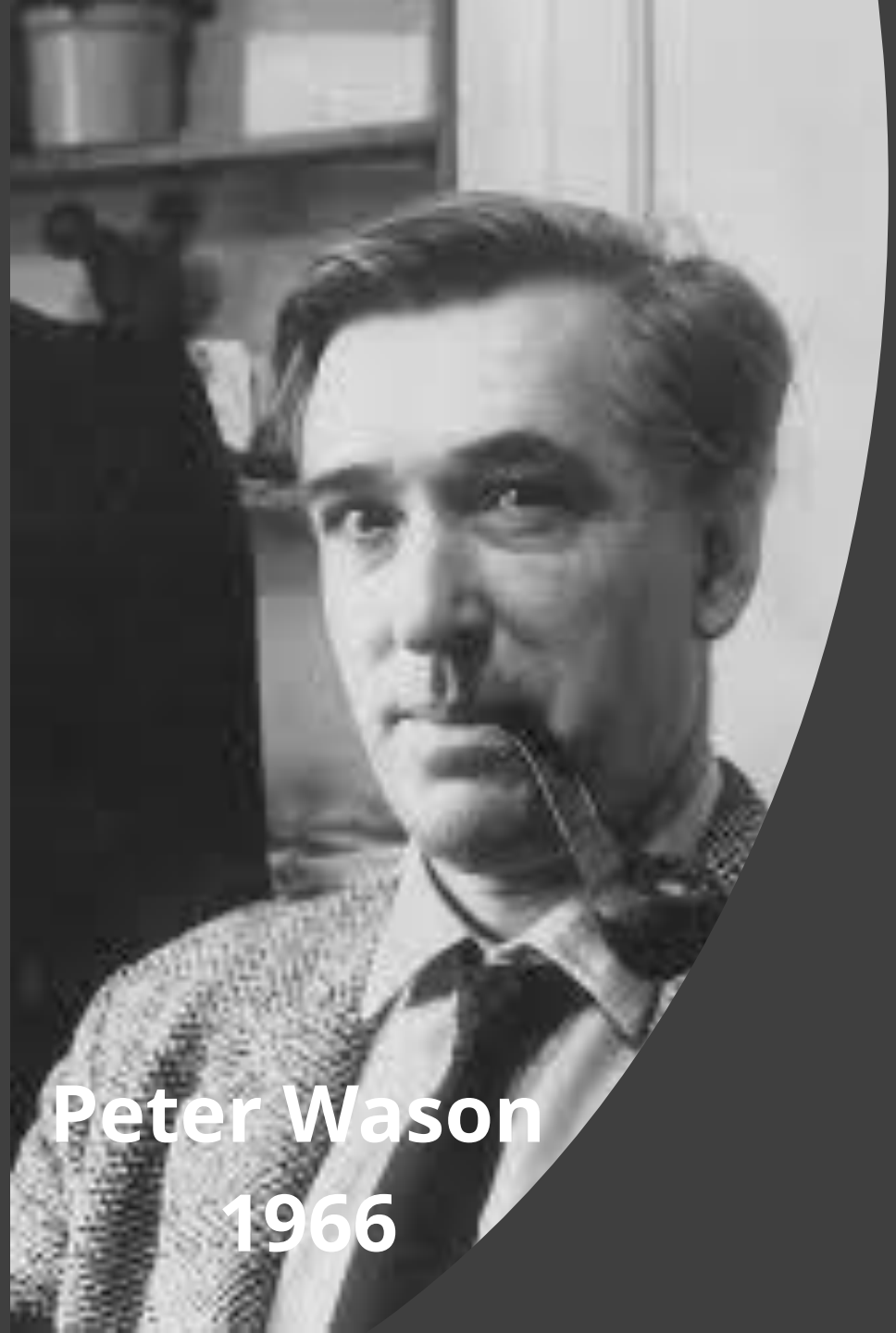
Comparison of physician and artificial intelligence-based symptom checker diagnostic accuracy

Markus Gräf[1,2] · Johannes Knitza[1,2,3] · Jan Leipe[4] · Martin Krusche[5] · Martin Welcker[6] · Sebastian Kuhn[7] · Johanna Mucke[8] · Axel J. Hueber[1,9] · Johannes Hornig[10] · Philipp Klemm[11] · Stefan Kleinert[12] · Peer Aries[13] · Nicolas Vuillerme[3,14,15] · David Simon[1,2] · Arnd Kleyer[1,2] · Georg Schett[1,2] · Johanna Callhoff[16,17]

Received: 19 July 2022 / Accepted: 29 August 2022 / Published online: 10 September 2022

Abstract

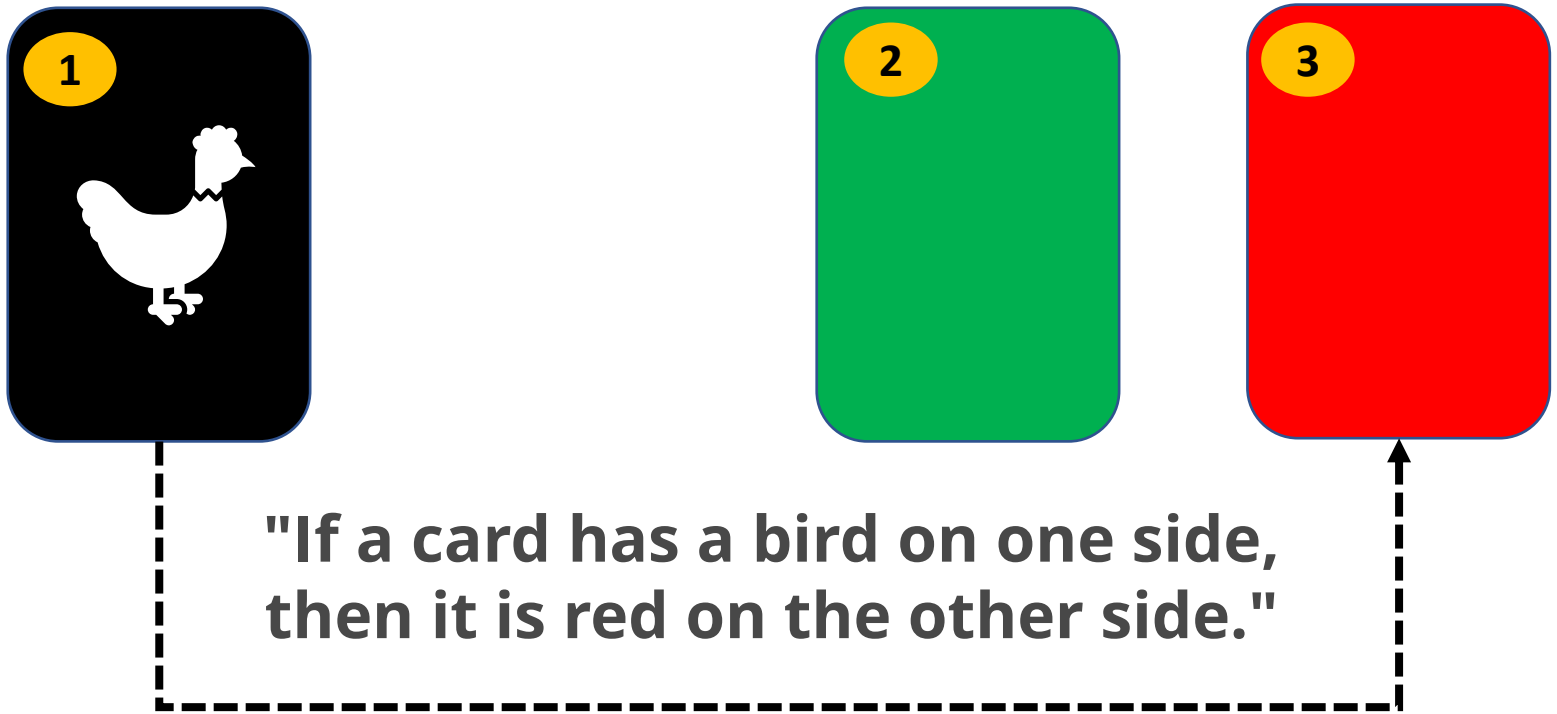
Symptom checkers are increasingly used to assess new symptoms and navigate the health care system. The aim of this study was to compare the accuracy of an artificial intelligence (AI)-based symptom checker (Ada) and physicians regarding the presence/absence of an inflammatory rheumatic disease (IRD). In this survey study, German-speaking physicians with prior rheumatology working experience were asked to determine IRD presence/absence and suggest diagnoses for 20 different real-world patient vignettes, which included only basic health and symptom-related medical history. IRD detection rate and suggested diagnoses of participants and Ada were compared to the gold standard, the final rheumatologists' diagnosis, reported on the discharge summary report. A total of 132 vignettes were completed by 33 physicians (mean rheumatology working experience 8.8 (SD 7.1) years). Ada's diagnostic accuracy (IRD) was significantly higher compared to physicians (70 vs 54%, $p=0.002$) according to top diagnosis. Ada listed the correct diagnosis more often compared to physicians (54 vs 32%, $p<0.001$) as top diagnosis as well as among the top 3 diagnoses (59 vs 42%, $p<0.001$). Work experience was not related to suggesting the correct diagnosis or IRD status. Confined to basic health and symptom-related medical history, the diagnostic accuracy of physicians was lower compared to an AI-based symptom checker. These results highlight the potential of using symptom checkers early during the patient journey and importance of access to complete and sufficient patient information to establish a correct diagnosis.



Peter Wason
1966

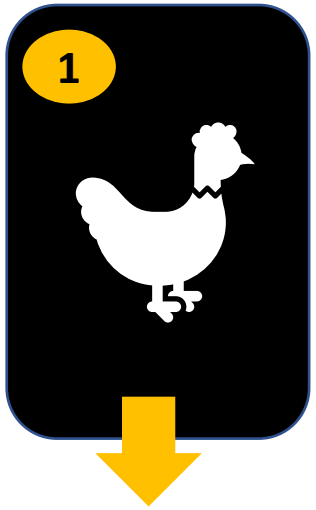
Deductive inference

TESTING COGNITIVE BIASES BY PETER WASON

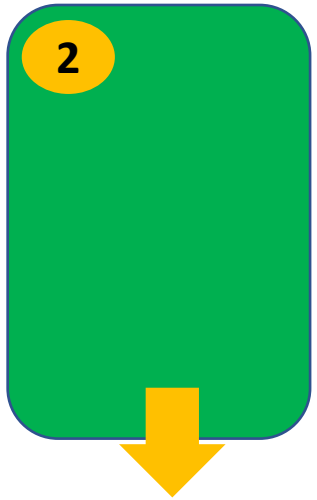


Which 2 cards should you turn over to determine the veracity of the rule

❑ **Card 1** ❑ **Card 2** ❑ **Card 3**



✓ ❑ Card 1
✓ ❑ Card 2
❑ Card 3



Red

Non-Bird

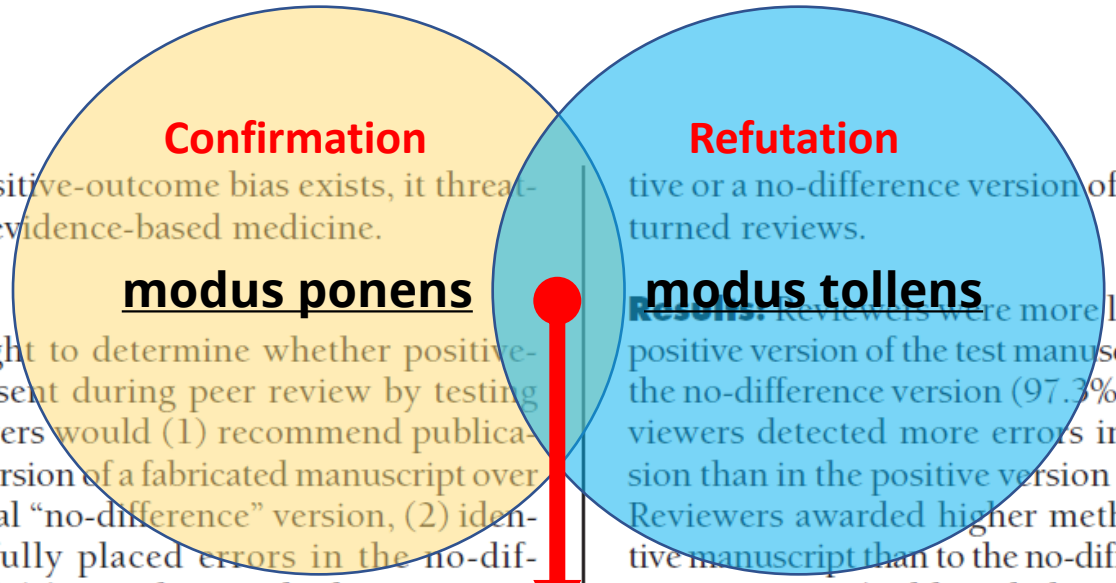
The most common mistake:
flip red-card and forget green-card

We trend to look more for a verification than a refutation of a rule (here, forget the green-card)

Testing for the Presence of Positive-Outcome Bias in Peer Review

A Randomized Controlled Trial

Gwendolyn B. Emerson, MD; Winston J. Warme, MD; Fredric M. Wolf, PhD; James D. Heckman, MD; Richard A. Brand, MD; Seth S. Leopold, MD



Background: If positive-outcome bias exists, it threatens the integrity of evidence-based medicine.

Methods: We sought to determine whether positive-outcome bias is present during peer review by testing whether peer reviewers would (1) recommend publication of a "positive" version of a fabricated manuscript over an otherwise identical "no-difference" version, (2) identify more purposefully placed errors in the no-difference version, and (3) rate the "Methods" section in the positive version more highly than the identical "Methods" section in the no-difference version. Two versions of a well-designed randomized controlled trial that differed only in the direction of the finding of the principal study end point were submitted for peer review to 2 journals in 2008-2009. Of 238 reviewers for *The Journal of Bone and Joint Surgery* and *Clinical Orthopaedics and Related Research* randomly allocated to review either a positive or a no-difference version of the manuscript, 210 returned reviews.

Results: Reviewers were more likely to recommend the positive version of the test manuscript for publication than the no-difference version (97.3% vs 80.0%, $P<.001$). Reviewers detected more errors in the no-difference version than in the positive version (0.85 vs 0.41, $P<.001$). Reviewers awarded higher methods scores to the positive manuscript than to the no-difference manuscript (8.24 vs 7.53, $P=.005$), although the "Methods" sections in the 2 versions were identical.

Conclusions: Positive-outcome bias was present during peer review. A fabricated manuscript with a positive outcome was more likely to be recommended for publication than was an otherwise identical no-difference manuscript.

Arch Intern Med. 2010;170(21):1934-1939

Bayesian inference

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

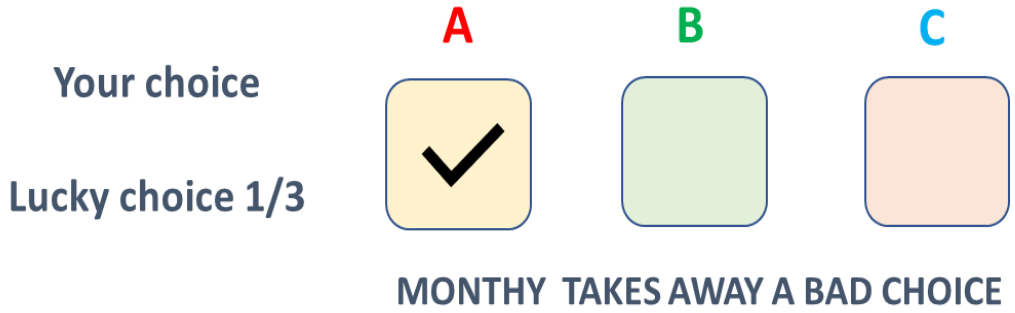
General population : (Prevalence) % sick people

→Cancer 10% →Other 60%

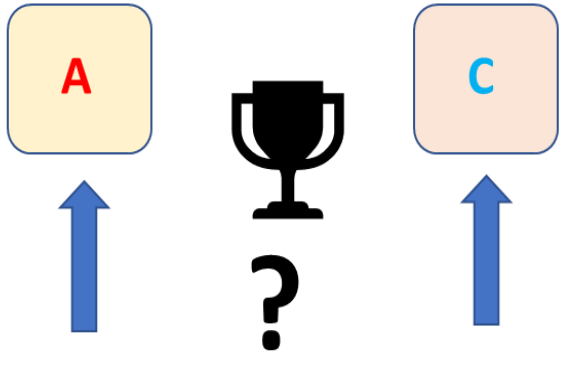
Diagnosis' Test accuracy:	Cancer	Other
Sensitivity	90%	50%
Specificity	90%	50%

Odds (PPV) to be sick if the diagnosis test is positive

PPV	Cancer	Other
90%		
80%	?	
70%		
60%		
50%		



New choice Probability ?



- ❑ 33%
- ❑ 50%
- ❑ 66%

$$PPV = \frac{\text{sensitivity} \times \text{prevalence}}{[\text{sensitivity} \times \text{prevalence}] + [(1-\text{specificity}) \times (1-\text{prevalence})]}$$

$$NPV = \frac{\text{specificity} \times (1-\text{prevalence})}{[(1-\text{sensitivity}) \times \text{prevalence}] + [\text{specificity} \times (1-\text{prevalence})]}$$

General population : (Prevalence) % sick people

→ Cancer 10% → Other 60%

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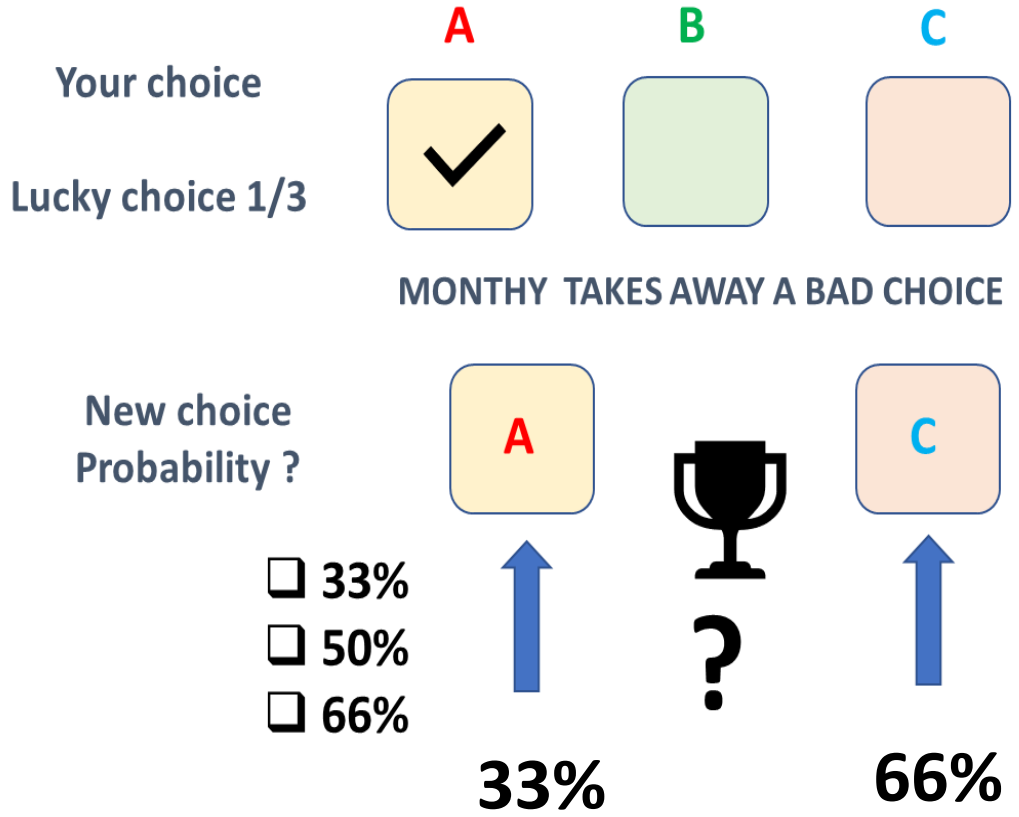
Odds (PPV) to be sick if the diagnosis test is positive

PPV	Cancer	Other
90%		
80%		
70%		
60%		60%
50%	50%	

JCI The Journal of Clinical Investigation
Published by The American Society for Clinical Investigation | Founded 1908

There's a goat behind door number 3: from Monty Hall to medicine

David J. Friedman,[1] Laurence A. Turka,[1,2] and Simon C. Robson[1]



Cognitive illusions could be just a game

But, unfortunately

They distort our health policies

Expert reports and Health autority guidelines overide causal reasoning

Prostate cancer is not recommended to screen prostate cancer in asymptomatic men but should be use in a symptomatic man

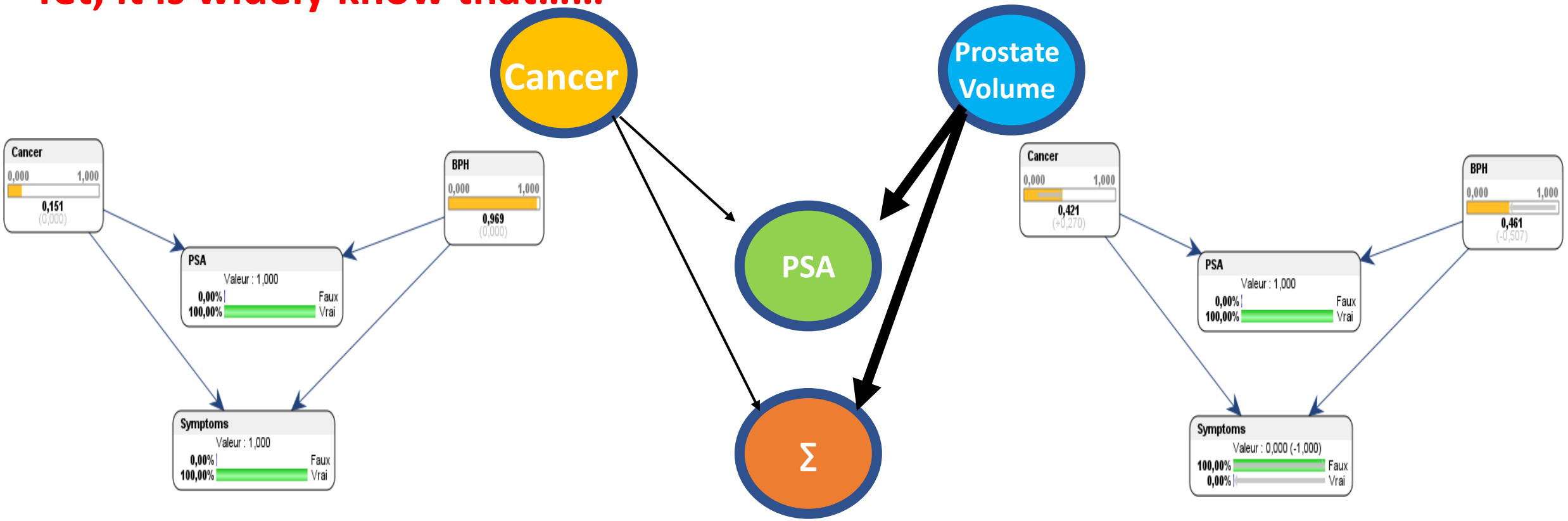
PSA assay is not recommended to screen prostate cancer in the general population or in populations of men considered more at risk

The use of 5αreductase inhibitors increases the risk of prostate cancer worse outcome

Health authorities

« Prostate cancer should be sought in a symptomatic man"

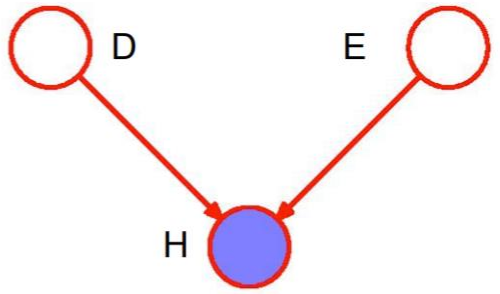
Yet, it is widely know that……



Berkson Joseph
1899 -1982

Survival of the Berkson' selection bias (1946)

	E^+		E^-	
	D^+	D^-	D^+	D^-
H^+	800	600	400	200
H^-	200	400	600	800



- The prevalence of the disease (***D***) is 50% among exposed (***E***) and unexposed.
- 70% are hospitalized (***H***) among exposed patients (30% among non exposed)
- 60% are hospitalized among diseased patients (40% among non diseased).

- **Within those hospitalized**, the prevalence of the disease is 57% among exposed and 66% among unexposed patients.

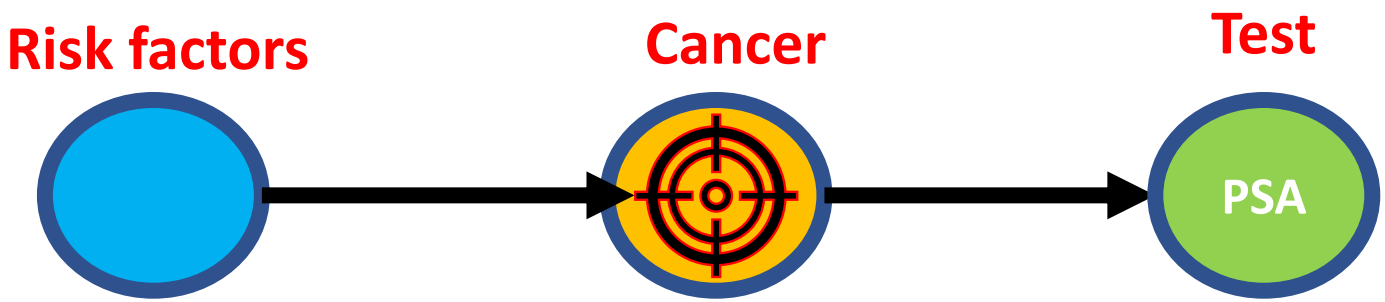
nature COMMUNICATIONS **2020**

Collider bias undermines our understanding of COVID-19 disease risk and severity

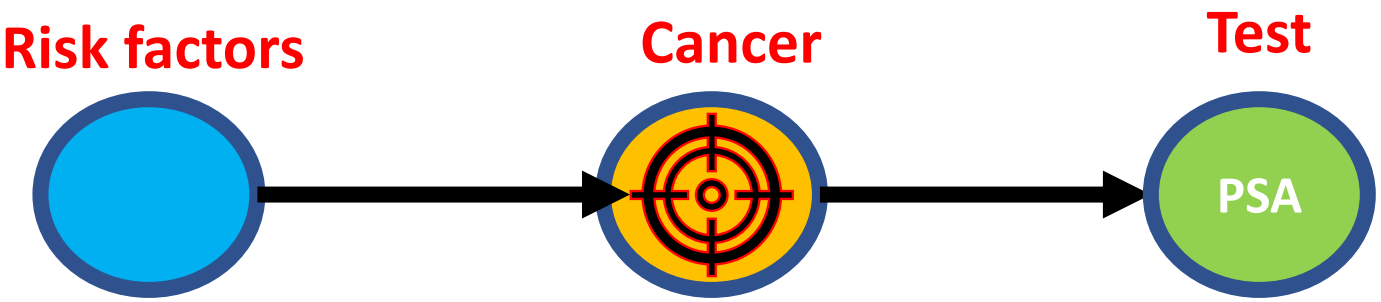
Gareth J. Griffith[1,2,4], Tim T. Morris[1,2,4], Matthew J. Tudball[1,2,4], Annie Herbert[1,2,4], Giulia Mancano[1,2,4], Lindsey Pike[1,2], Gemma C. Sharp[1,2], Jonathan Sterne[2], Tom M. Palmer[1,2], George Davey Smith[1,2], Kate Tilling[1,2], Luisa Zuccolo[1,2], Neil M. Davies[1,2,3] & Gibran Hemani[1,2,4]✉

Screening for prostate cancer in populations of men with risk factors

Health authorities

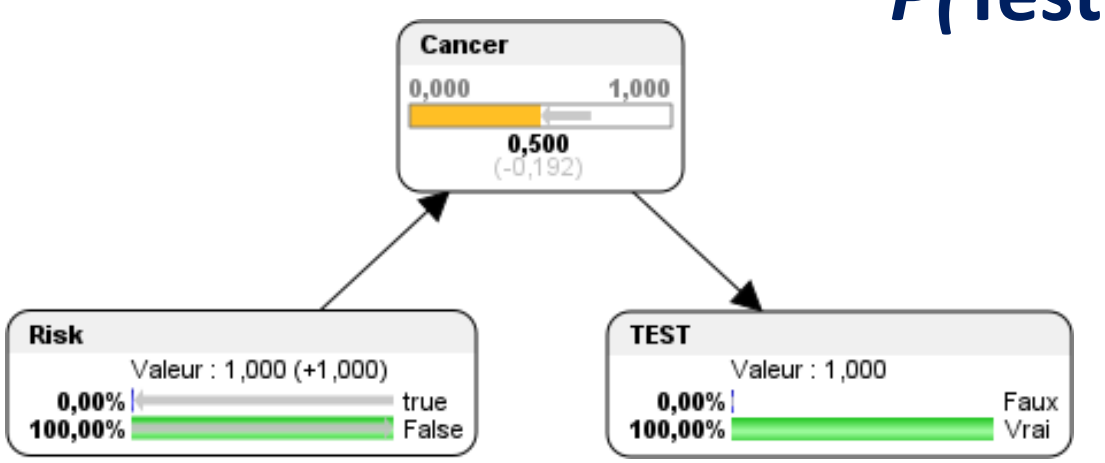


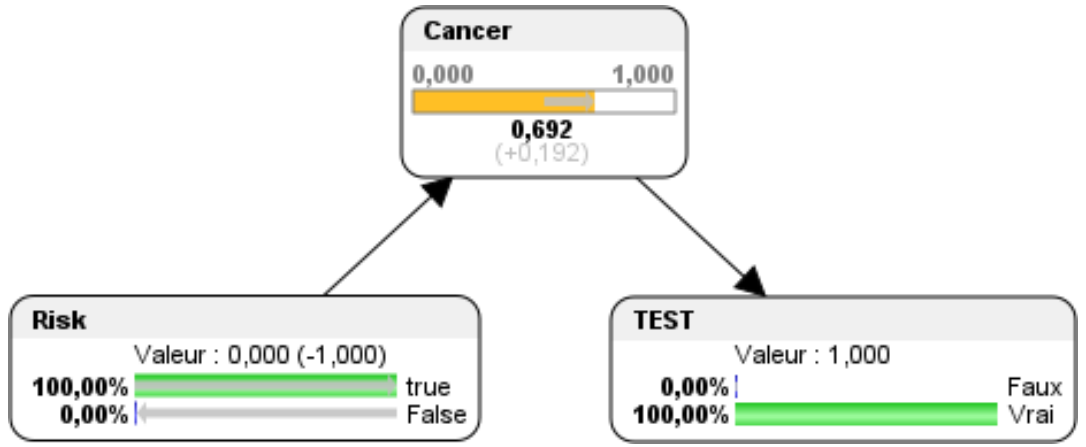
The High Authority for Health recalls that current knowledge does not allow to recommend screening for prostate cancer by PSA assay systematically in the general population or in populations of men considered more at risk.



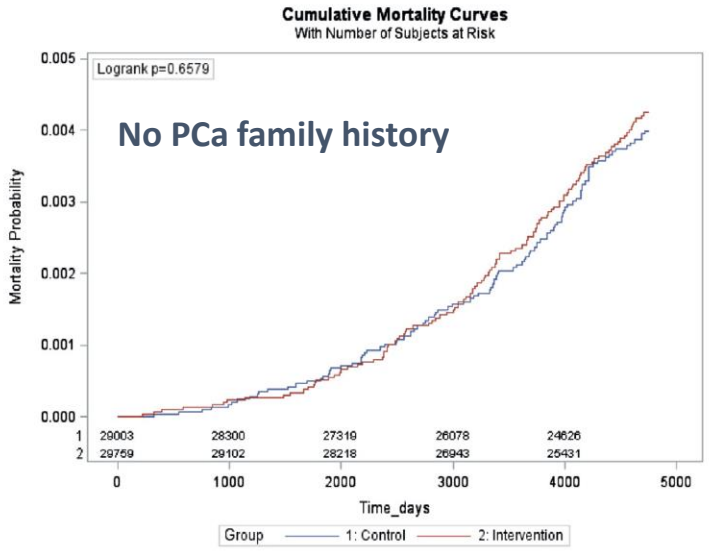
Screening for prostate cancer in populations of men with risk factors

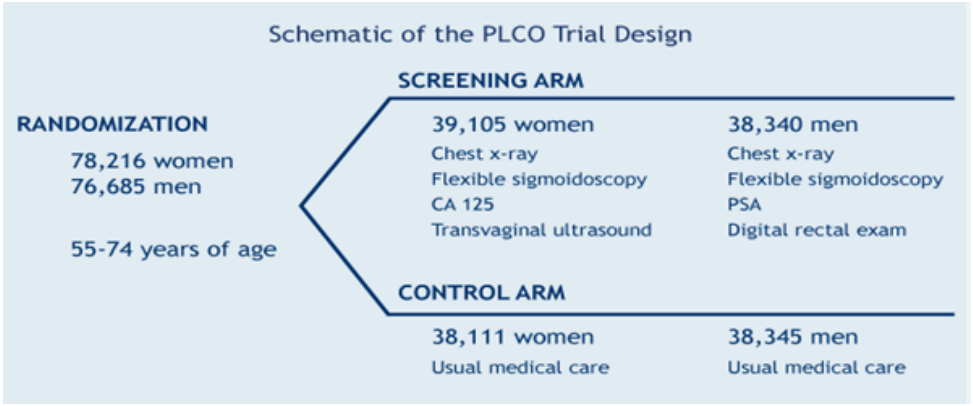
$$P(\text{Cancer}^+/\text{Test}^+) = \frac{P(\text{Test}^+/\text{Cancer}^+) \times P(\text{Cancer}^+)}{P(\text{Test}+)}$$





Prostate, Lung, Colorectal, and Ovarian Cancer Screening Trial (PLCO)

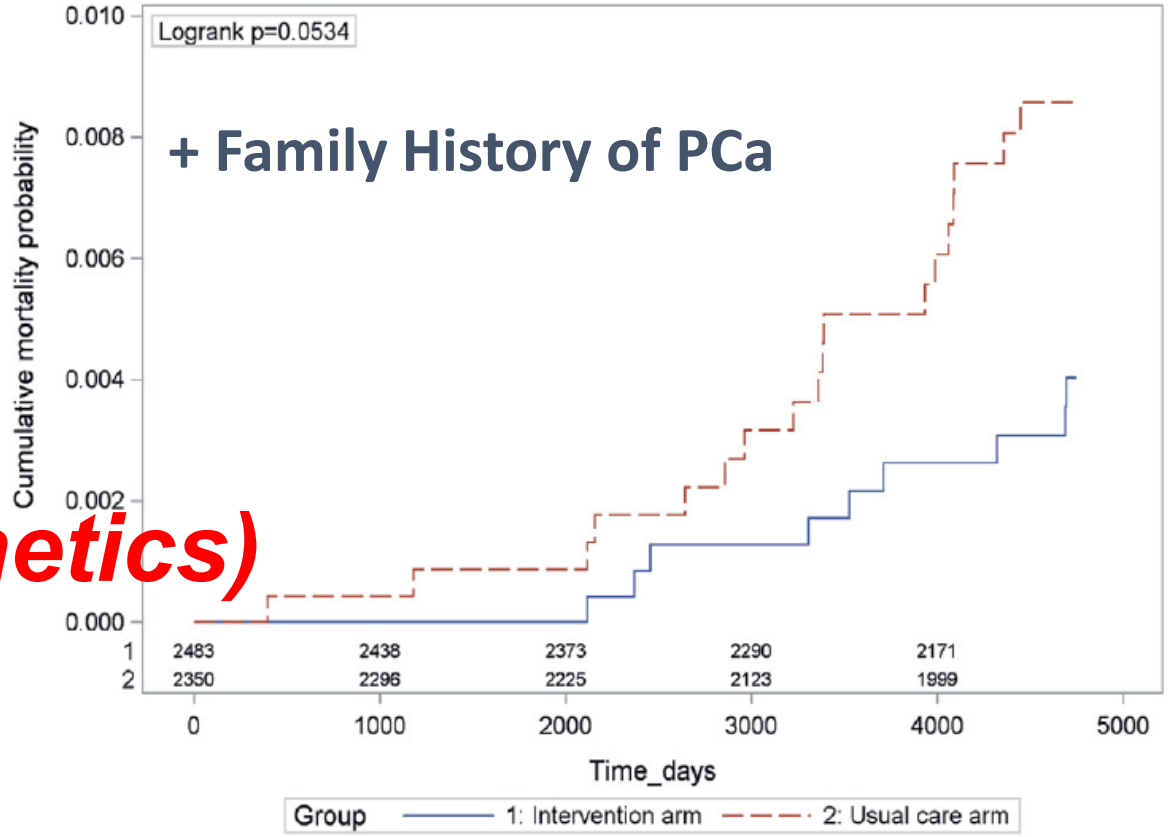




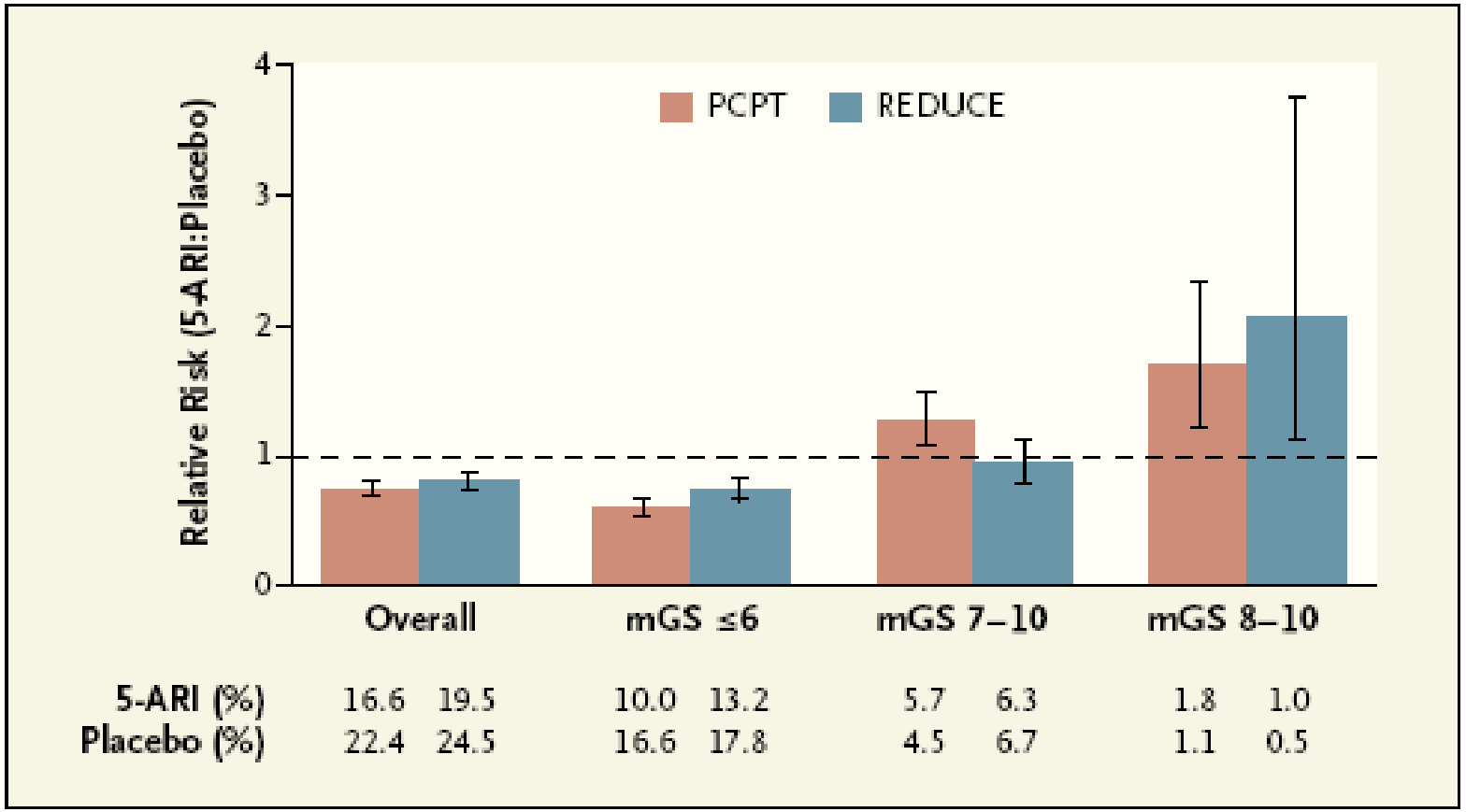
However …….

Impact of family history on prostate cancer mortality in white men undergoing prostate specific antigen based screening.
Liss MA, et al J Urol. 2015.

(↓ † >50% if FR genetics)



Prostate cancer prevention using 5 αReductase inhibitors (5ARi)



Relative and Absolute Risk of Prostate Cancer According to Modified Gleason Score (mGS), PCPT and REDUCE Trial.

Health authorities → **Increase aggressiveness of cancer**

But.....

=5ARi drug

Effect of Finasteride on the Sensitivity of PSA for Detecting Prostate Cancer

Ian M. Thompson, Chen Chi, Donna Pauler Ankerst, Phyllis J. Goodman, Catherine M. Tangen, Scott M. Lippman, M. Scott Lucia, Howard L. Parnes, Charles A. Coltman, Jr.

Journal of the National Cancer Institute, Vol. 98, No. 16, August 16, 2006

Background: **In the Prostate Cancer Prevention Trial (PCPT), men receiving finasteride had a 24.8% lower risk of prostate cancer than men receiving placebo but a higher risk of high-grade cancer. We examined the impact of finasteride on the sensitivity and area under the receiver operating characteristic curve (AUC) of prostate-specific antigen (PSA) for detecting prostate cancer.** ***Methods:*** **We studied men in the placebo and finaste and concur pared the p AUC of PS son grade 7 PSA cutoffs matched by specificity.** ***Conclusions:*** **PSA had statistically significantly better sensitivity and AUC for detecting prostate cancer in the finasteride arm of the PCPT than in the placebo arm. This bias would be expected to contribute to greater detection of all grades of prostate cancer with finasteride. [J Natl Cancer Inst 2006;98:1128–33]**

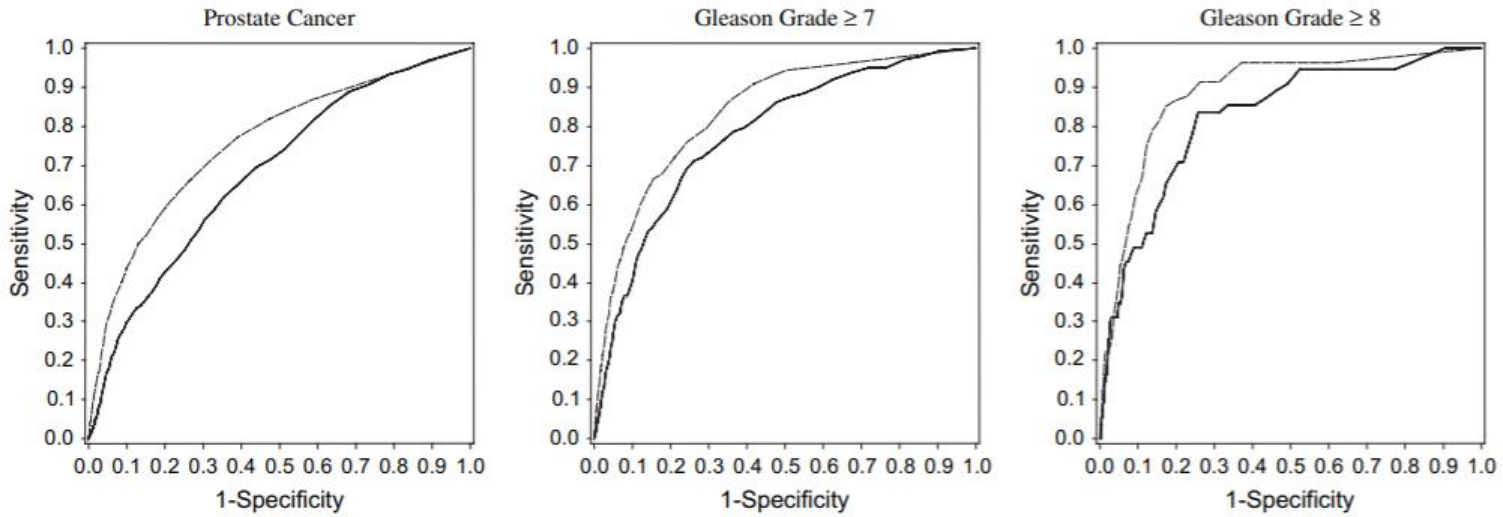
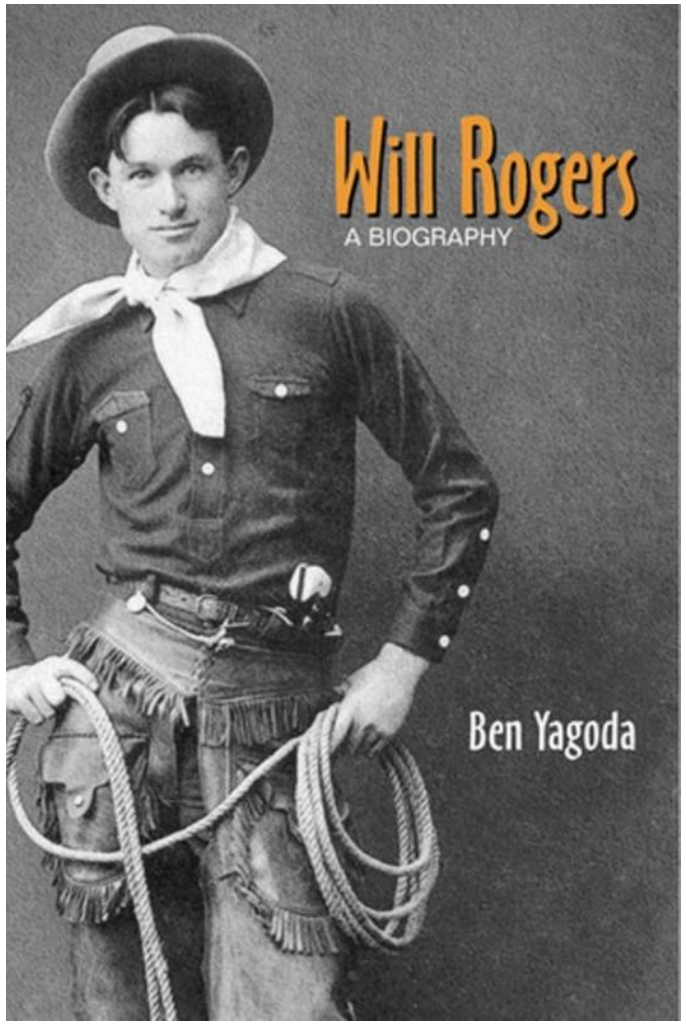


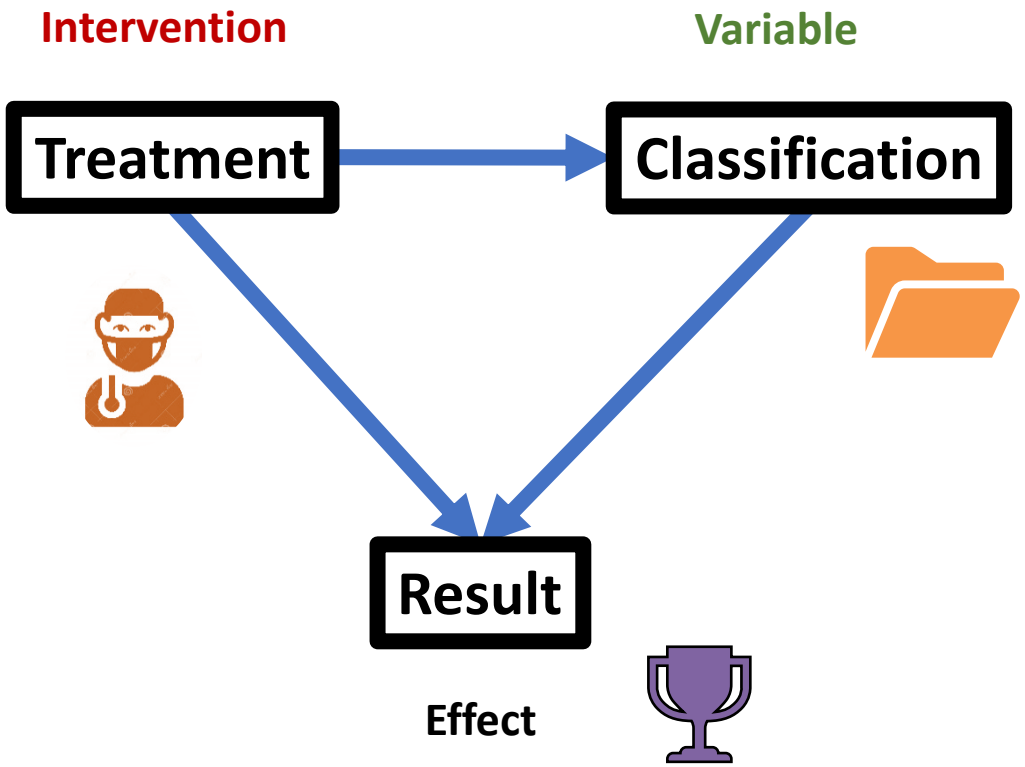
Fig. 1. Receiver operating characteristic (ROC) curves for prostate-specific antigen detection of all prostate cancer and high-grade prostate cancer. **Left**, ROC curves for all prostate cancer; **middle**, ROC curves for Gleason grade 7 or higher prostate cancer; **right**, ROC curves for Gleason grade 8 or higher prostate cancer. **Solid line** = placebo group; **dashed line** = finasteride group. *P* values for difference between placebo and finasteride groups [from test of DeLong et al. *(3)*] are <.001 for all prostate cancer, .003 for Gleason grade 7 or higher prostate cancer, and .071 for Gleason grade 8 or higher prostate cancer.

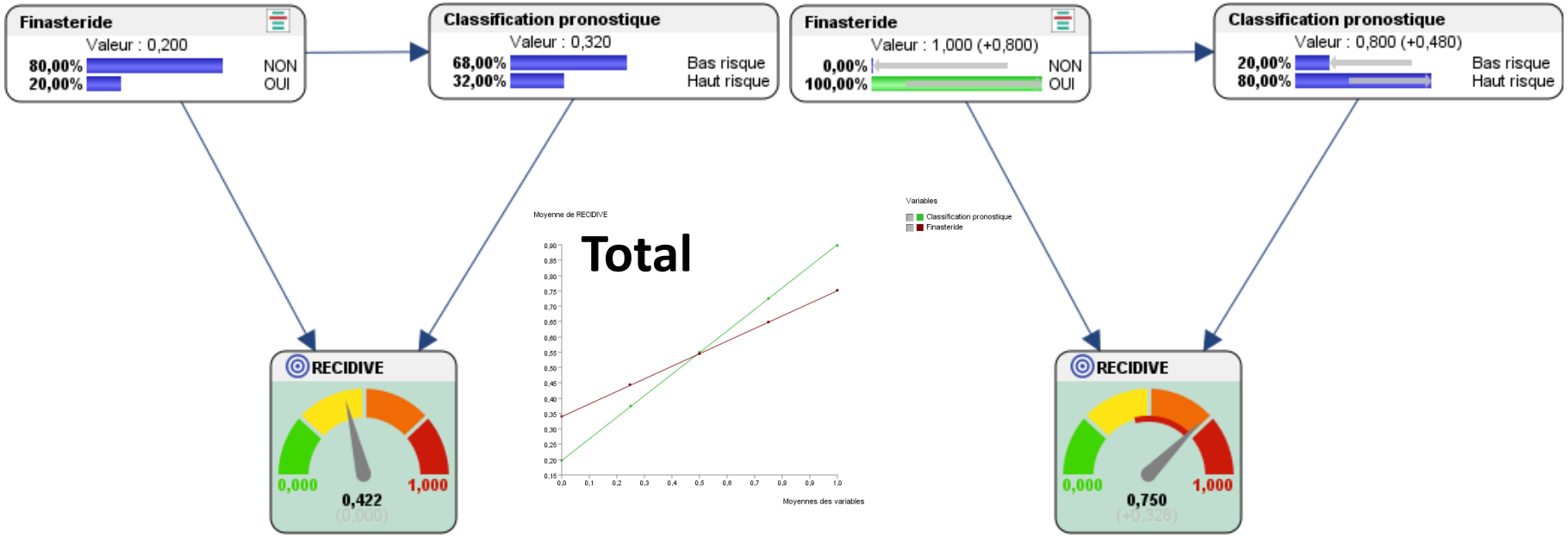
The Will Rogers Phenomenon — Stage Migration and New Diagnostic Techniques as a Source of Misleading Statistics for Survival in Cancer

Alvan R. Feinstein, M.D., Daniel M. Sosin, M.D., and Carolyn K. Wells, M.P.H.

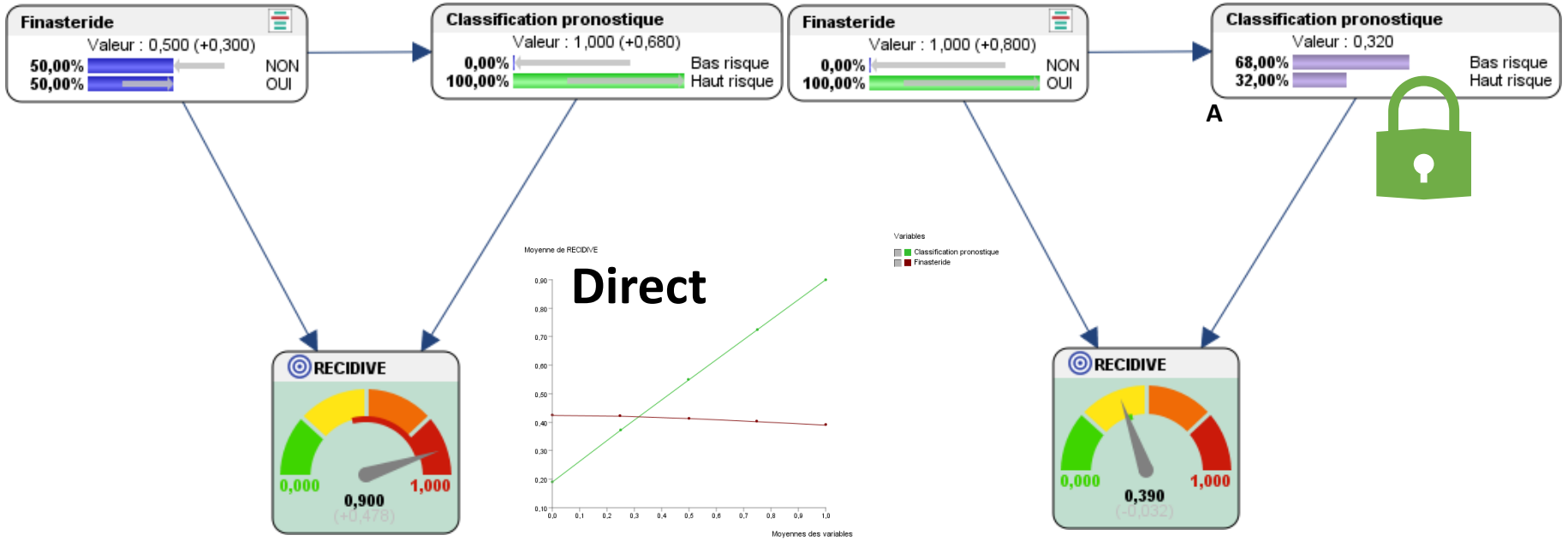


N Engl J Med 1985; 312:1604-1608





Total



Direct

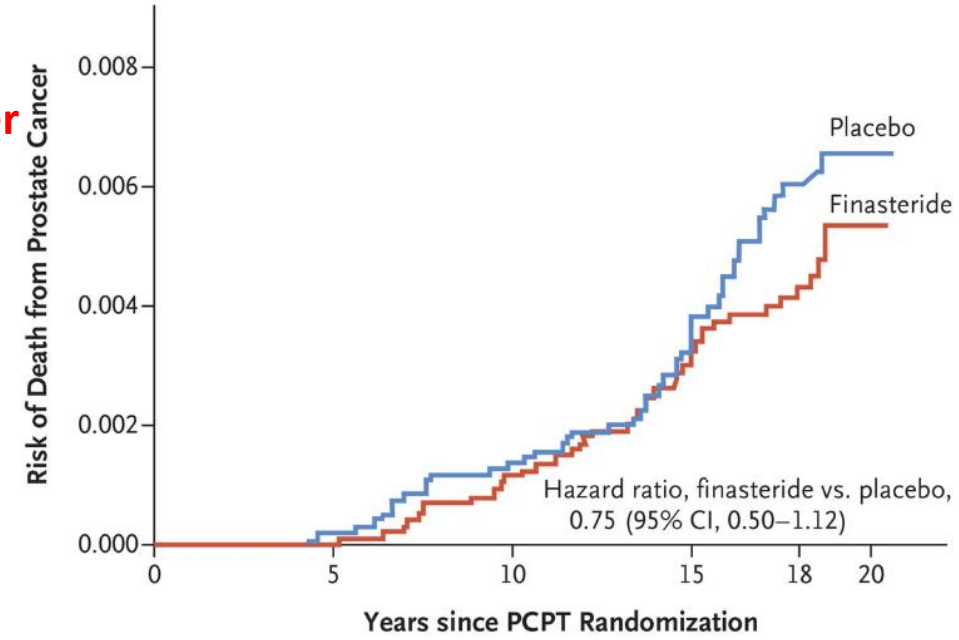
The NEW ENGLAND JOURNAL of MEDICINE

January 24, 2019
N Engl J Med 2019; 380:393-394

CORRESPONDENCE FREE PREVIEW

Long-Term Effects of Finasteride on Prostate Cancer Mortality

Here again, 20 years later



Variable	Placebo	Finasteride
Total eligible randomized patients	9457	9423
Follow-up for patients still alive (yr)		
Median	18.4	18.4
Interquartile range	17.4–18.7	17.3–18.7
Deaths (total no.)	2979	3048
Death from prostate cancer	56	42
Gleason score at diagnosis		
≤6	16	7
7	9	5
8–10	11	13
Unknown	20	17

	10 Yr	15 Yr	18 Yr
No. at Risk			
Placebo	8229	7094	4060
Finasteride	8198	7026	4012
Incidence (95% CI)			
Placebo	0.14% (0.07–0.23)	0.35% (0.25–0.49)	0.60% (0.45–0.78)
Finasteride	0.12% (0.06–0.21)	0.31% (0.21–0.44)	0.43% (0.31–0.59)

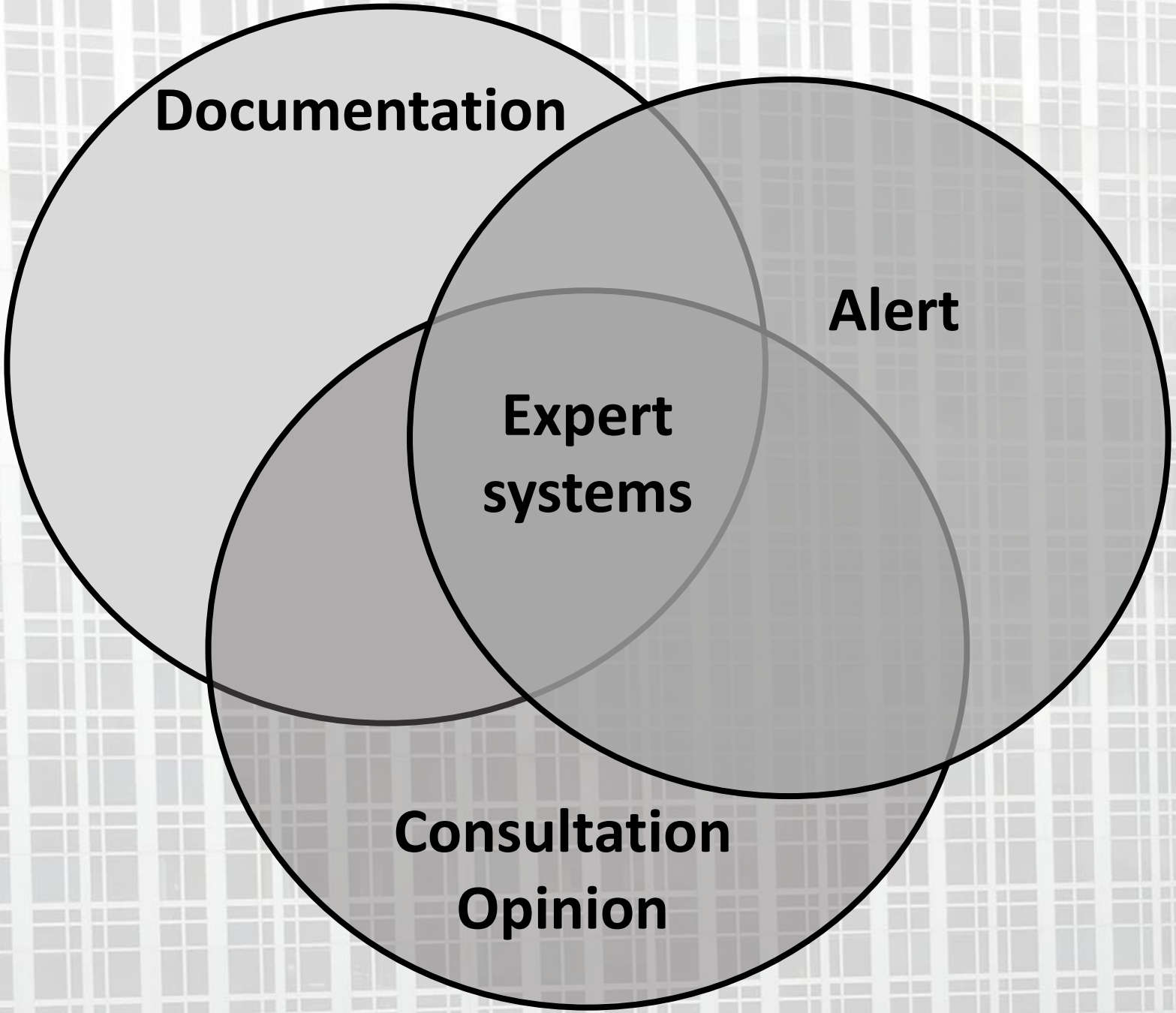
3-Algorithmic medicine and decision-making

Interactive computer-based decision-making systems

Bringing psychology closer to algorithms

Decision-making engine architecture

The « Integratome » experience in preventive medicine


Documentation
Alert
Expert
systems
Consultation
Opinion

We recommend that patients use this tool in consultation with their doctor.
This tool is only for use in men without metastatic disease where conservative management and radical treatment are both options being considered.

Reset

Age at diagnosis – +

PSA (ng/ml) – +

Clinical T stage 1 2 3 4

Hospital admission in last 2 years? No Yes

BRCA Negative or Untested Positive

Ethnic Origin Please click on the info button

Histological grade group 1 2 3 4 5

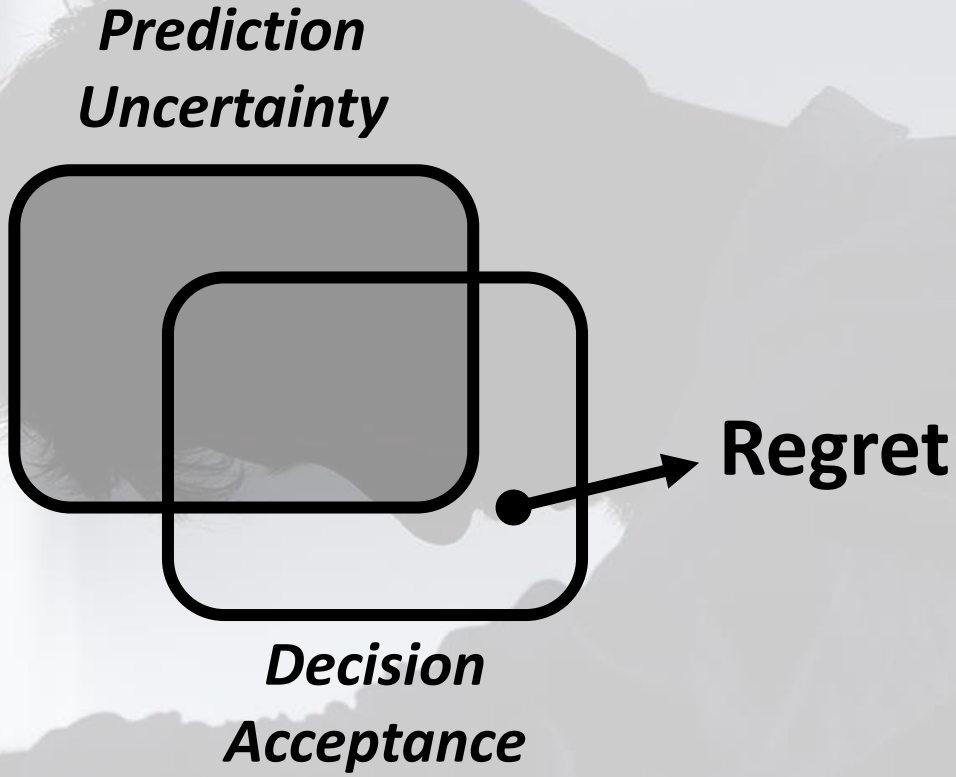
Gleason score 3+3 3+4 4+3 8 9 or 10

Biopsy data available? No Yes

Is there an intra-ductal carcinoma or invasive cribriform component reported in the biopsies? No Yes Unknown

Has the cancer spread (metastasis)? No Yes Unknown

The Best decision minimises regret

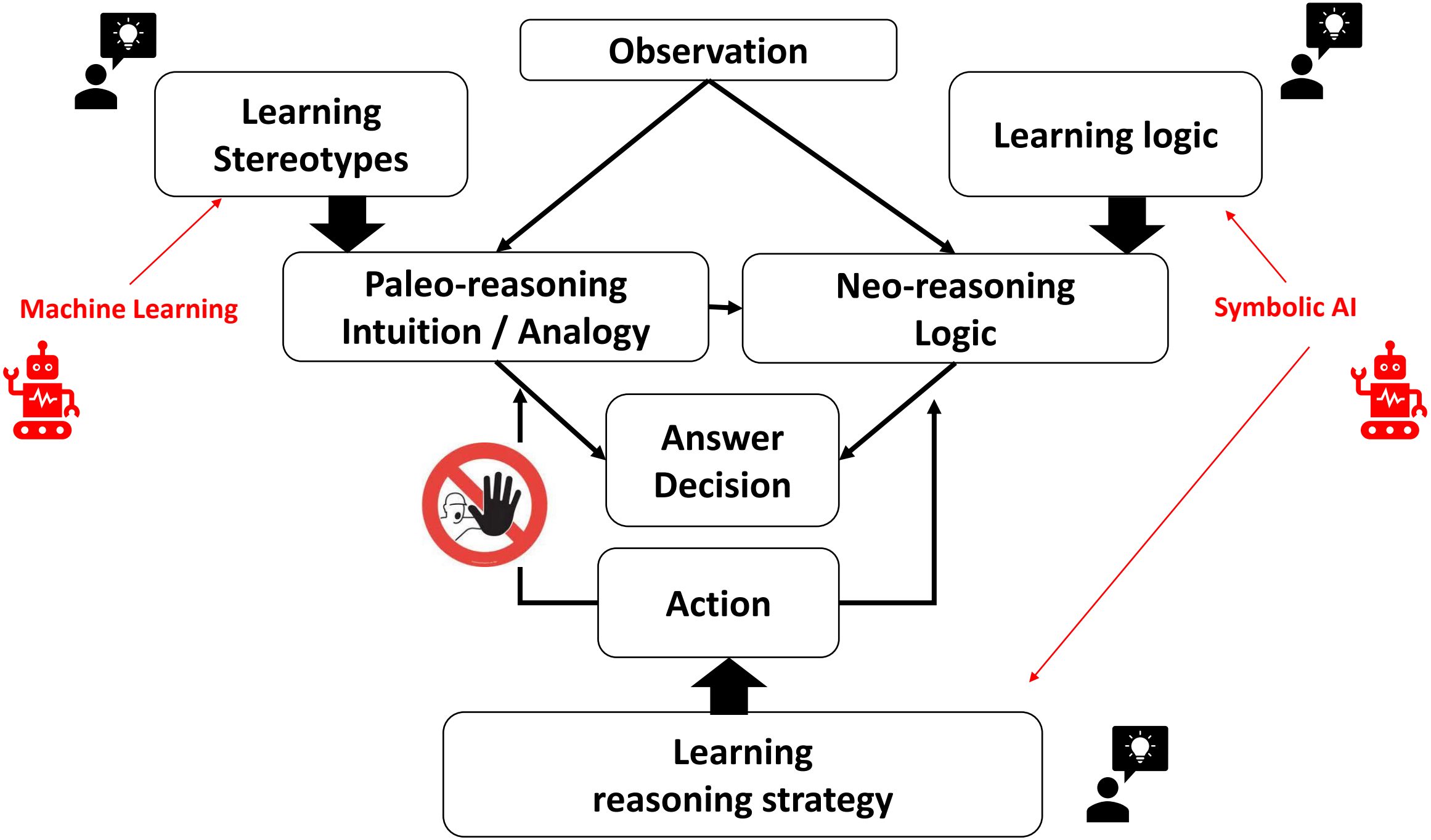


How cognitive illusions can be overcome.

System 1 operates automatically and cannot be turned off at will.

System 2 is too slow to serve as a permanent substitute for System 1

Can Artificial intelligence help ?


Observation
Learning Stereotypes
Learning logic
Machine Learning
Symbolic AI
Paleo-reasoning Intuition / Analogy
Neo-reasoning Logic
Answer Decision
Action
Learning reasoning strategy

DOI:10.1145/3241036

The kind of causal inference seen in natural human thought can be "algorithmitized" to help produce human-level machine intelligence.

BY JUDEA PEARL

The Seven Tools of Causal Inference, with Reflections on Machine Learning

THE DRAMATIC SUCCESS IN machine learning has led to an explosion of artificial intelligence (AI) applications and increasing expectations for autonomous systems that exhibit human-level intelligence. These expectations have, however, met with fundamental obstacles that cut across many application areas. One such obstacle

Intensive theoretical and experimental efforts toward "transfer learning," "domain adaptation," and "lifelong learning"[4] are reflective of this obstacle.

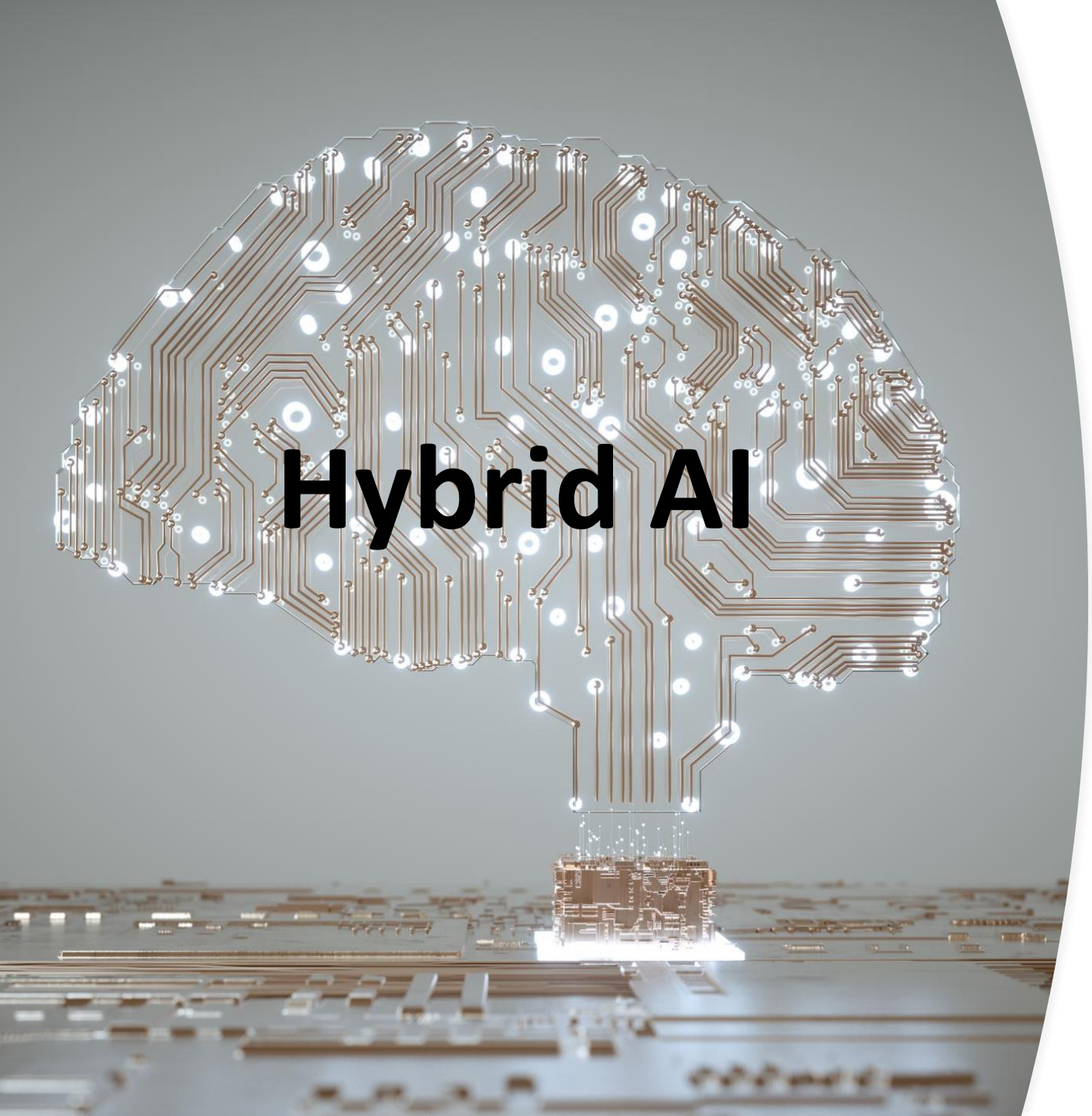
Another obstacle is "explainability," or that "machine learning models remain mostly black boxes"[26] unable to explain the reasons behind their predictions or recommendations, thus eroding users' trust and impeding diagnosis and repair; see Hutson[8] and Marcus.[11] A third obstacle concerns the lack of understanding of cause-effect connections. This hallmark of human cognition[10,23] is, in my view, a necessary (though not sufficient) ingredient for achieving human-level intelligence. This ingredient should allow computer systems to choreograph a parsimonious and modular representation of their environment, interrogate that representation, distort it through acts of imagination, and finally answer "What if?" kinds of questions. Examples include interventional questions: "What if I make it happen?" and retrospective or explanatory questions: "What if I had acted differently?" or "What if my flight had not been late?" Such questions cannot be articulated, let alone answered by systems that operate in purely statistical mode, as do most learning machines today. In this article, I show that all three obstacles can be overcome using causal modeling tools, in particular, causal diagrams and their associated logic. Central to the development of these tools are advances in graphical and structural models that have made counterfactuals computationally manageable and thus rendered causal reasoning a viable com-

» key insights

- Data science is a two-body problem, connecting data and reality, including the forces behind the data.
- Data science is the art of interpreting

Judea Pearl 1936-

	Mathematical **Reporting systems** *Psychological*		
Questions	***According to J. Pearl*** 	***According to D. Kahneman*** 	
What can I deduce from this by observing this? (ex: What does this sign tell me about this disease?)	**Associative calculated with machine learning systems** « SEEING »	**Automatic**	**Prediction**
What happens if I do this? (e.g. will this treatment be effective?)	**Interventional estimated by randomized trials or causal Bayesian networks** « DOING »	**Logic**	.....
What would have happened if I had done that? (e.g. is the therapeutic hazard observed due to my treatment?)	**Counterfactual calculated with functional models or structural equations** « IMAGINING »	**Executive**	**Decision**



Machine-learning

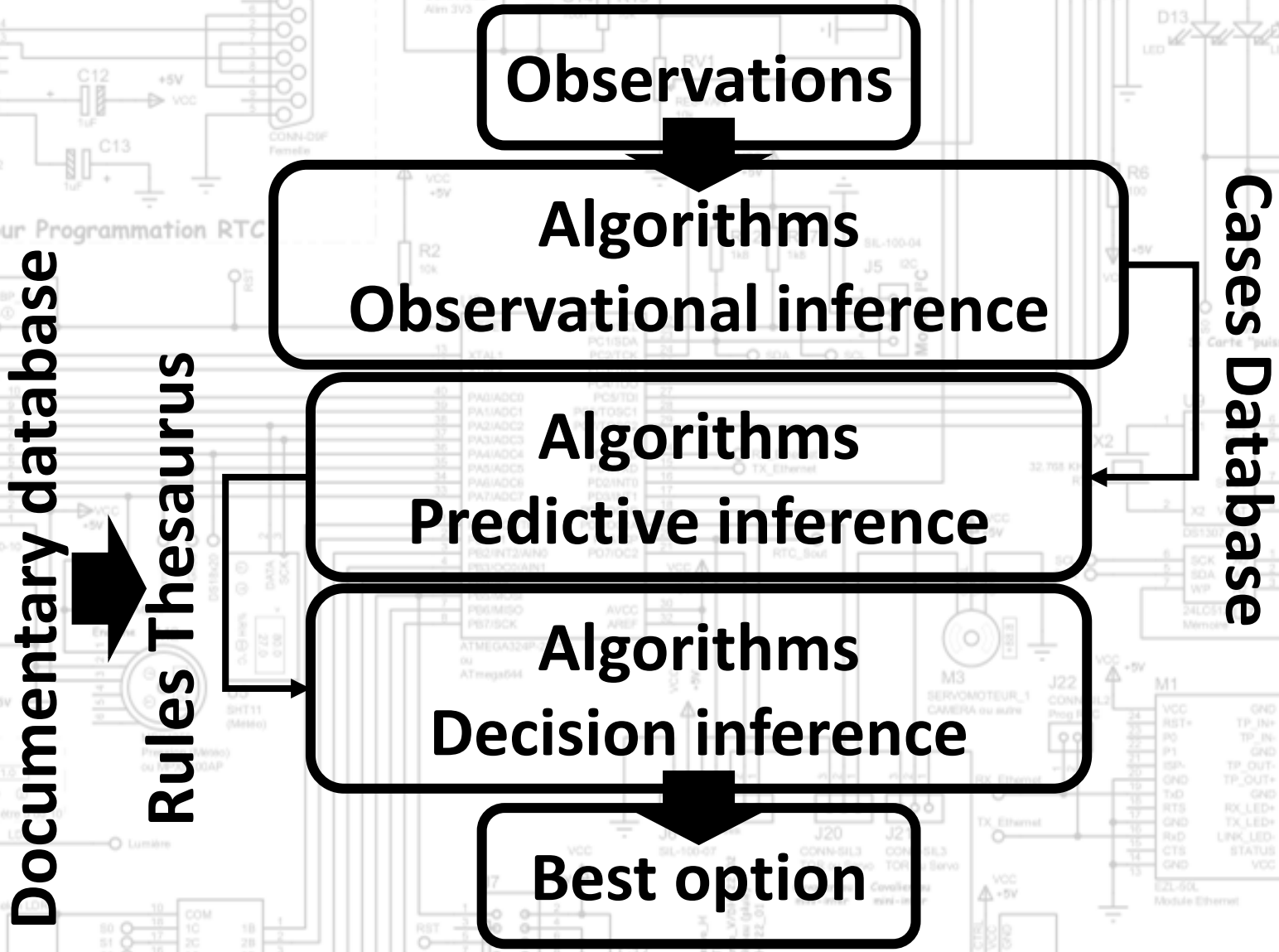
Deep-learning

+

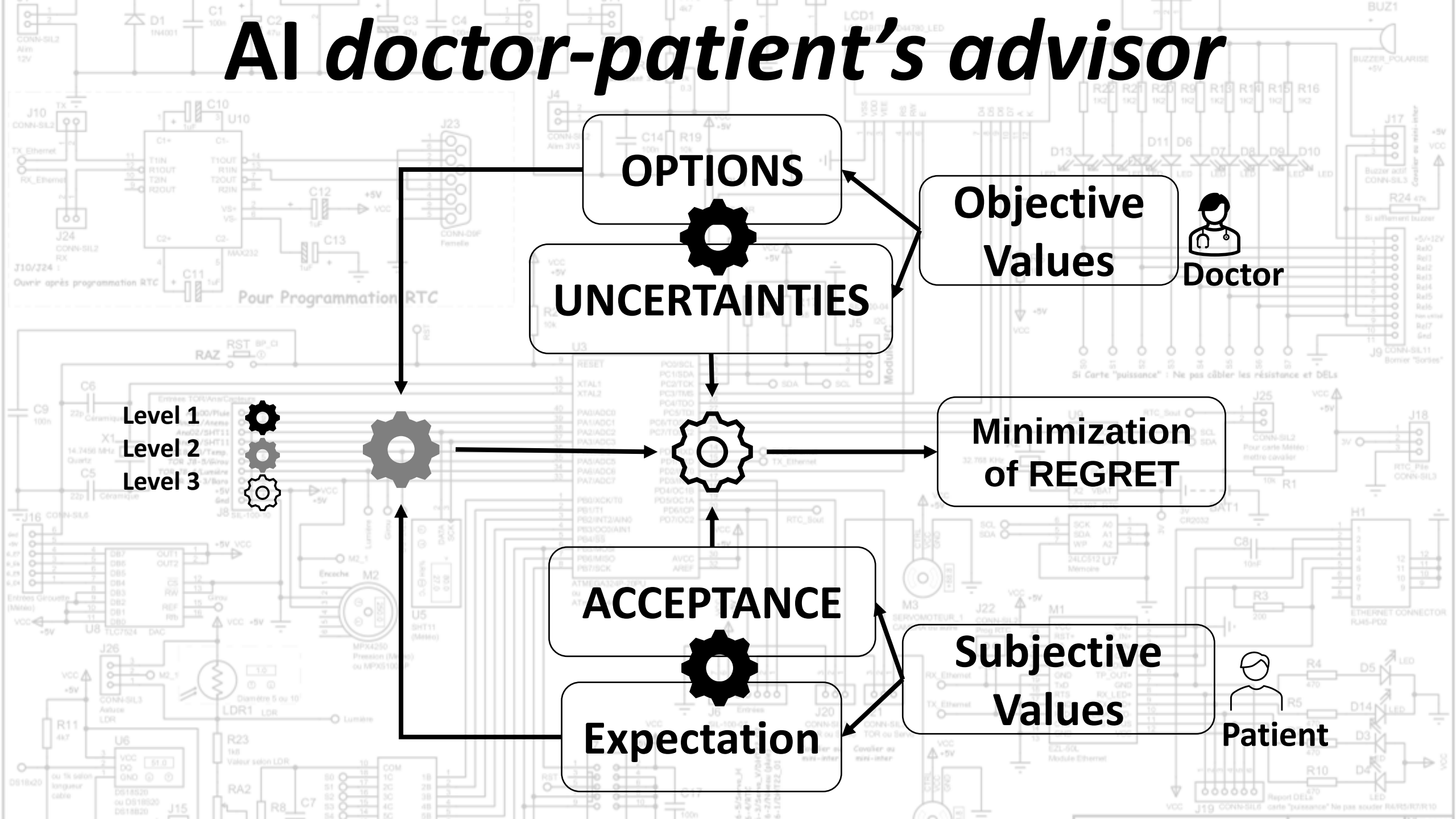
Symbolic AI

Involves the explicit embedding of human knowledge & behavior rules into computer

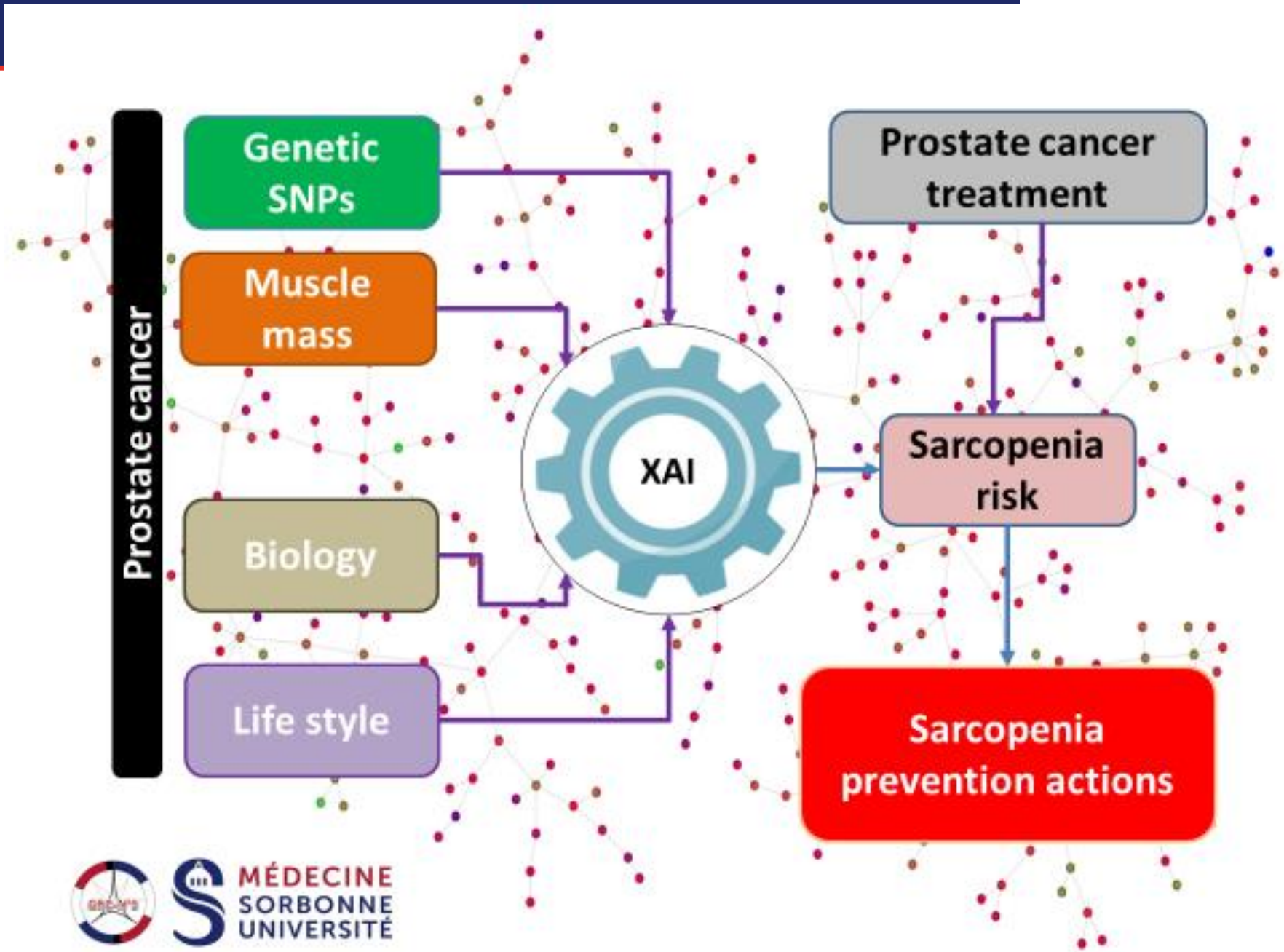
AI *doctor's assistant*



AI *doctor-patient's advisor*



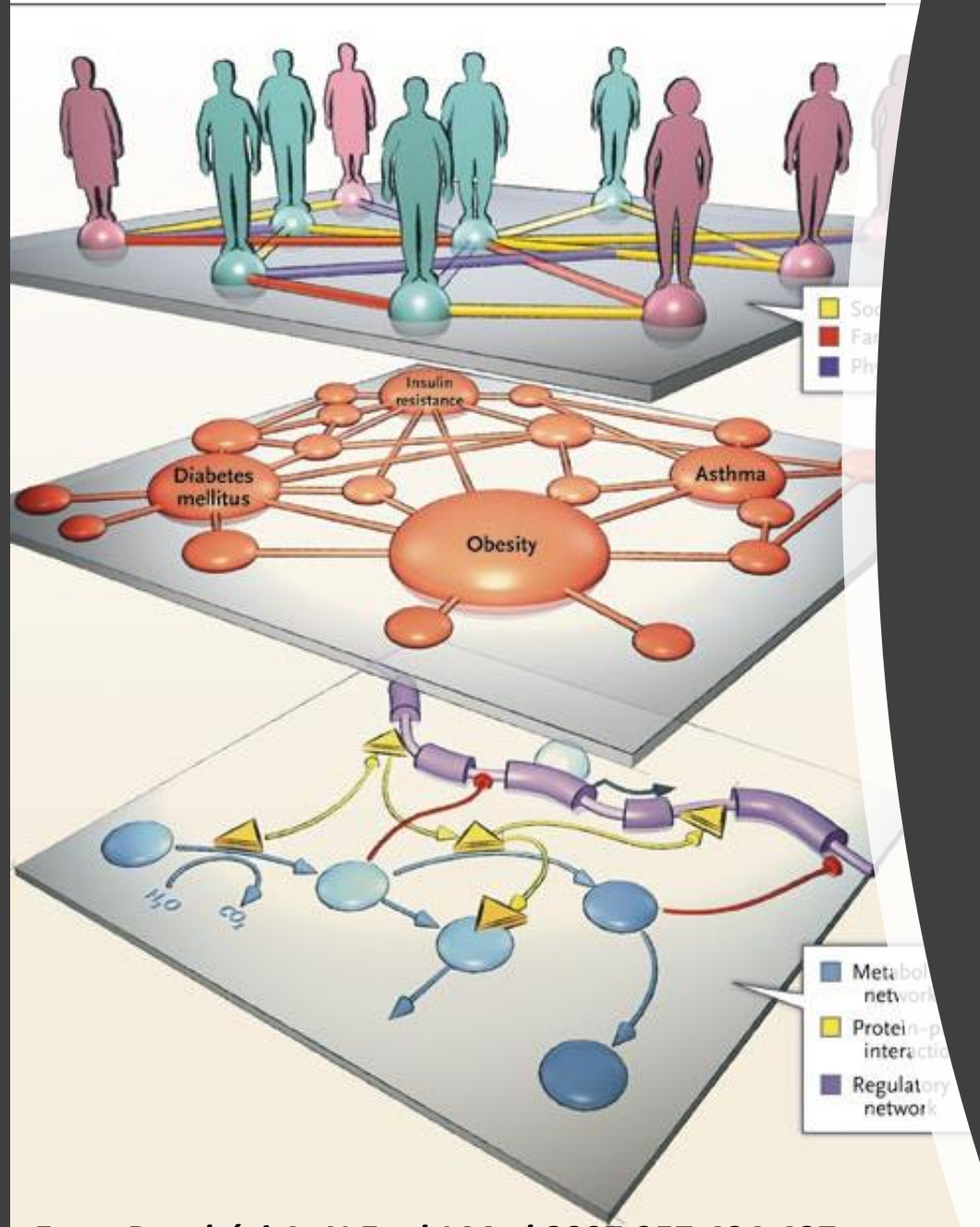
Cross-KIC EIT Health : un projet européen récompensé



Integratome

Holistic Medicine

Exploring with XAI the factors that influence the onset of the disease to provide insight into the mechanism of the disease and its points of attack to prevent it.



From Barabási A. N Engl J Med 2007;357:404-407.

Complex Networks for Precision Medicine

Most human diseases are not independent of each other, although they are often treated separately. diseases are associated with the breakdown of functional modules of relevant genetic, metabolic, and environnemental interactions. interrelationships among human diseases allow to construct a network in which two diseases are connected if they have a common genetic or environmental or functional links

Integratome
Holistic Medicine

Modelling preventive medicine

Case mix
Machine learning

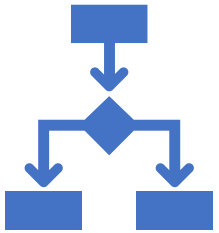
Customers
Expert

Medical literature
& guidelines

Boolean/Conditional rules
Decision tree

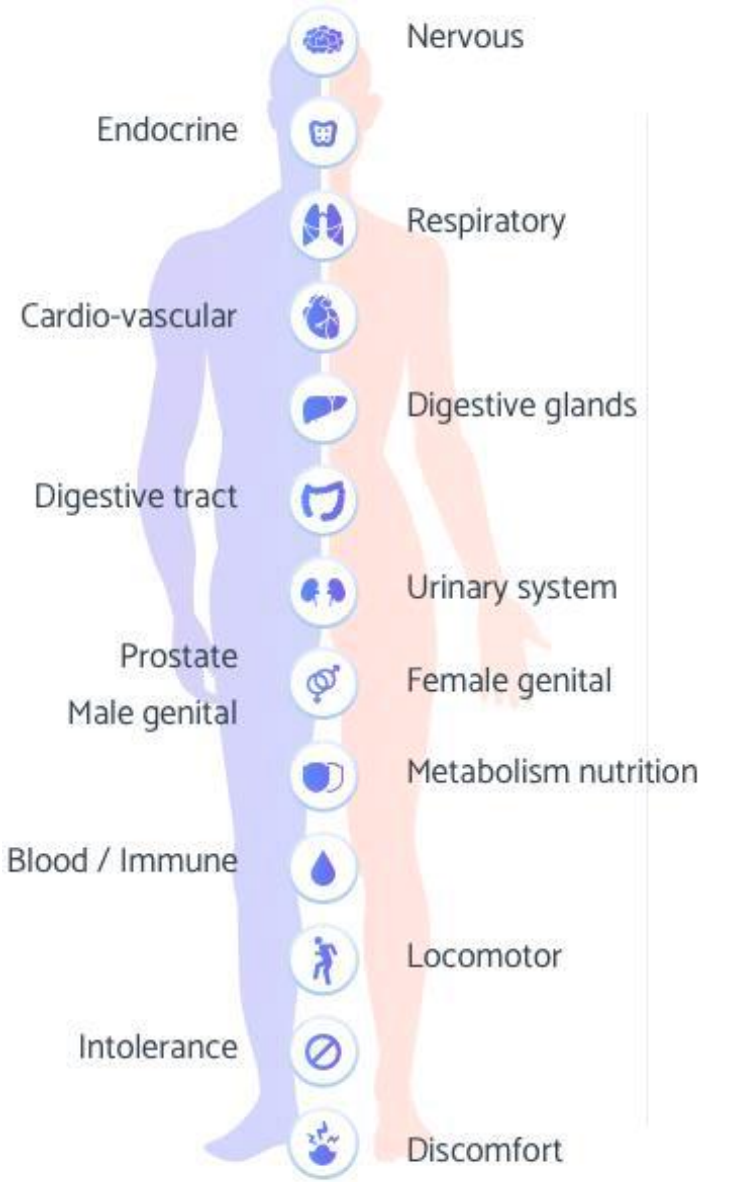
CUTOFFS

ACTIONS

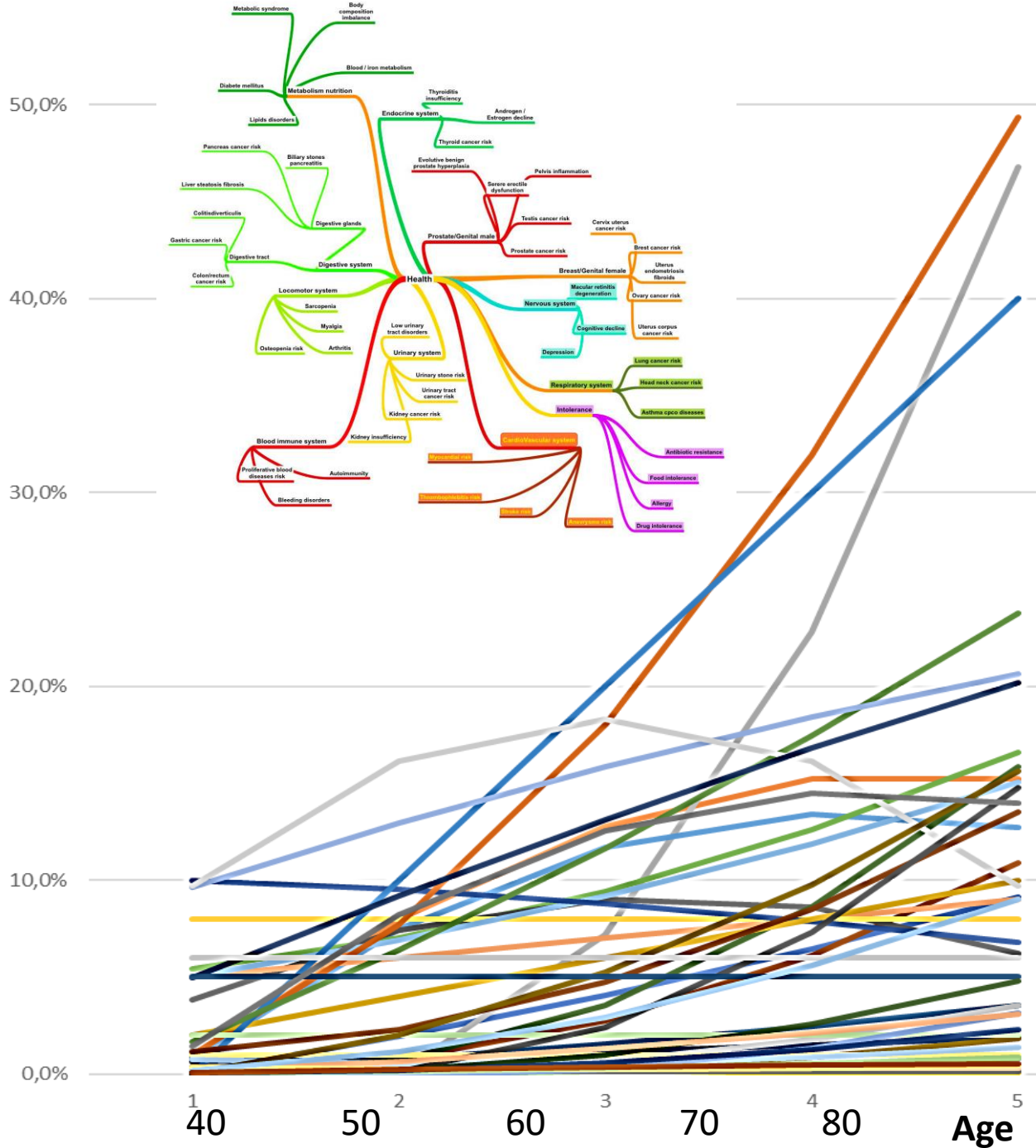


Integratome

Holistic Medicine

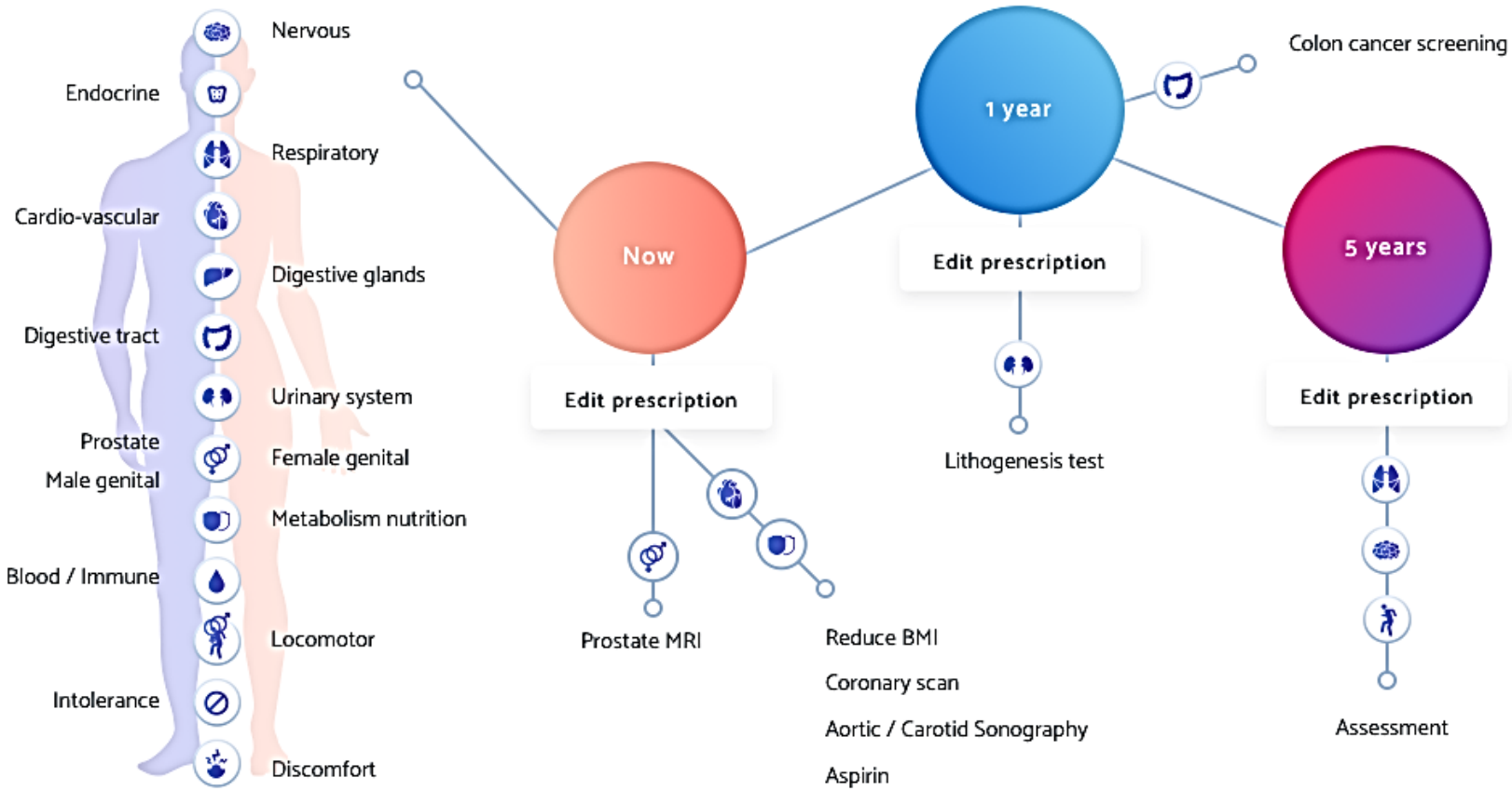


- Prostate cancerRisk
- Evolutive Benign Prostate Hyperplasia
- Severe Erectile dysfunction
- Testis cancerRisk
- Pelvis inflammation
- Low Urinary Tract Disorders
- Kidney cancerRisk
- Kidney insufficiency
- Urinary StoneRisk
- Urinary Tract TumorsRisk
- OsteopeniaRisk
- Sarcopenia
- Gastric cancerRisk
- Gastritis
- Colon cancerRisk
- Colitis/Diverticulosis
- Biliary stones/Pancreatitis
- Pancreas cancerRisk
- Liver steatosis/fibrosis
- Androgen decline
- Thyroid cancerRisk
- Thyroiditis/ insufficiency
- LIPIDS DISORDERS
- DIABETE Mellitus
- Metabolic syndrome
- Blood deficiency / Iron metabolism
- Body composition imbalance
- Bleeding disorders



Recommendations

Based on your informations



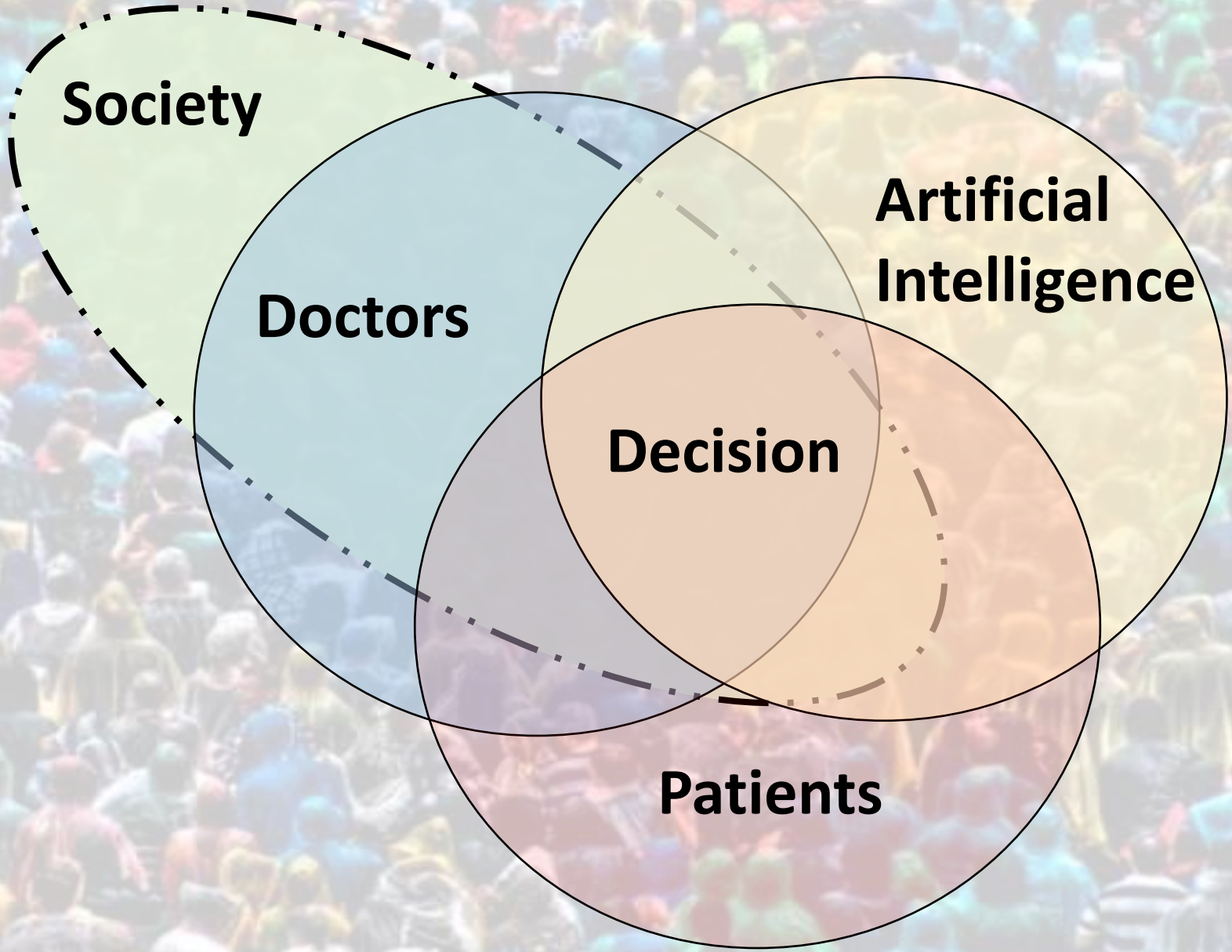
Additional analysis

Accurary

Data completion : 40%

Increase accuracy

4-Conclusion


Society
Doctors
Artificial Intelligence
Decision
Patients

Forbes

The Future Of Technology Support

Andrew Barlow Forbes Councils Member

Forbes Technology Council COUNCIL POST | Membership (Fee-Based)

Sep 3, 2020, 08:50am EDT

Technology Is On The Rise, While IQ Is On The Decline

Will Conaway Forbes Councils Member

Forbes Technology Council COUNCIL POST | Membership (Fee-Based)

POST WRITTEN BY

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CeRePP
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NUFFIELD DEPARTMENT OF SURGICAL SCIENCES

UNIVERSITY OF OXFORD