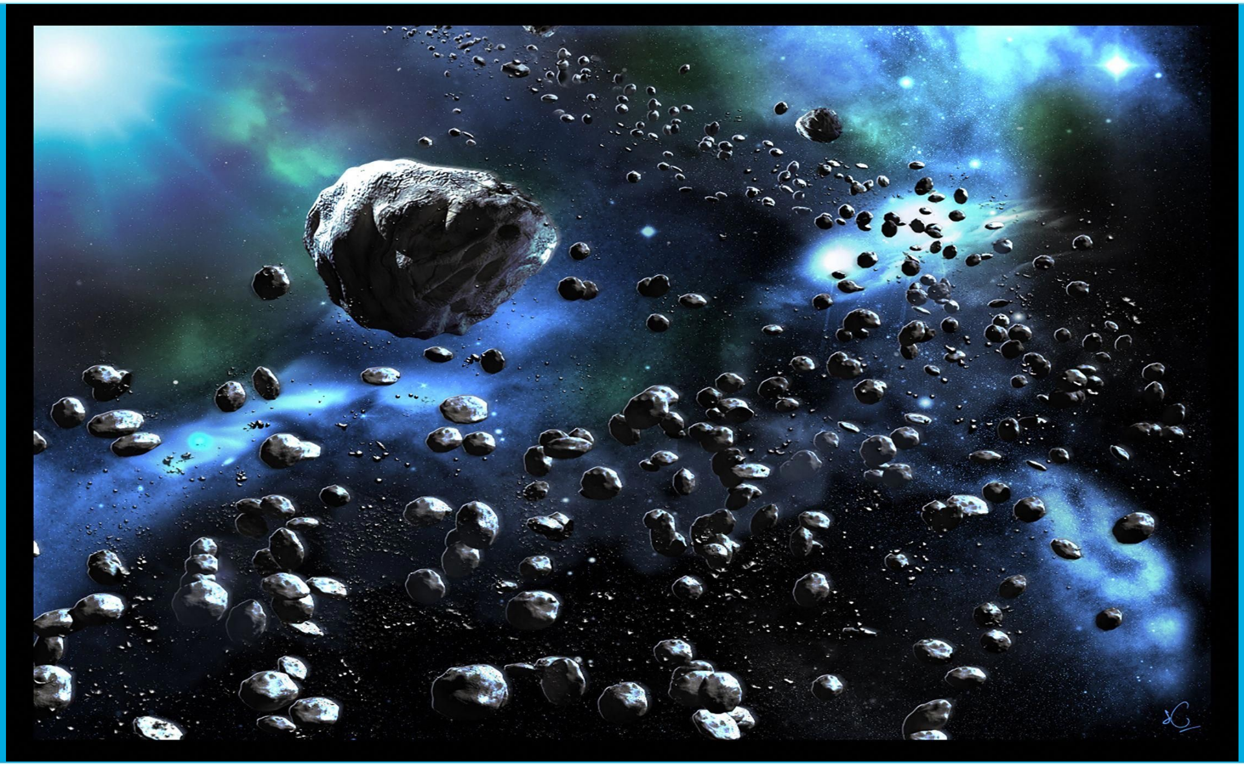

TO BOLDLY GO WHERE NO
ONE HAS GONE BEFORE

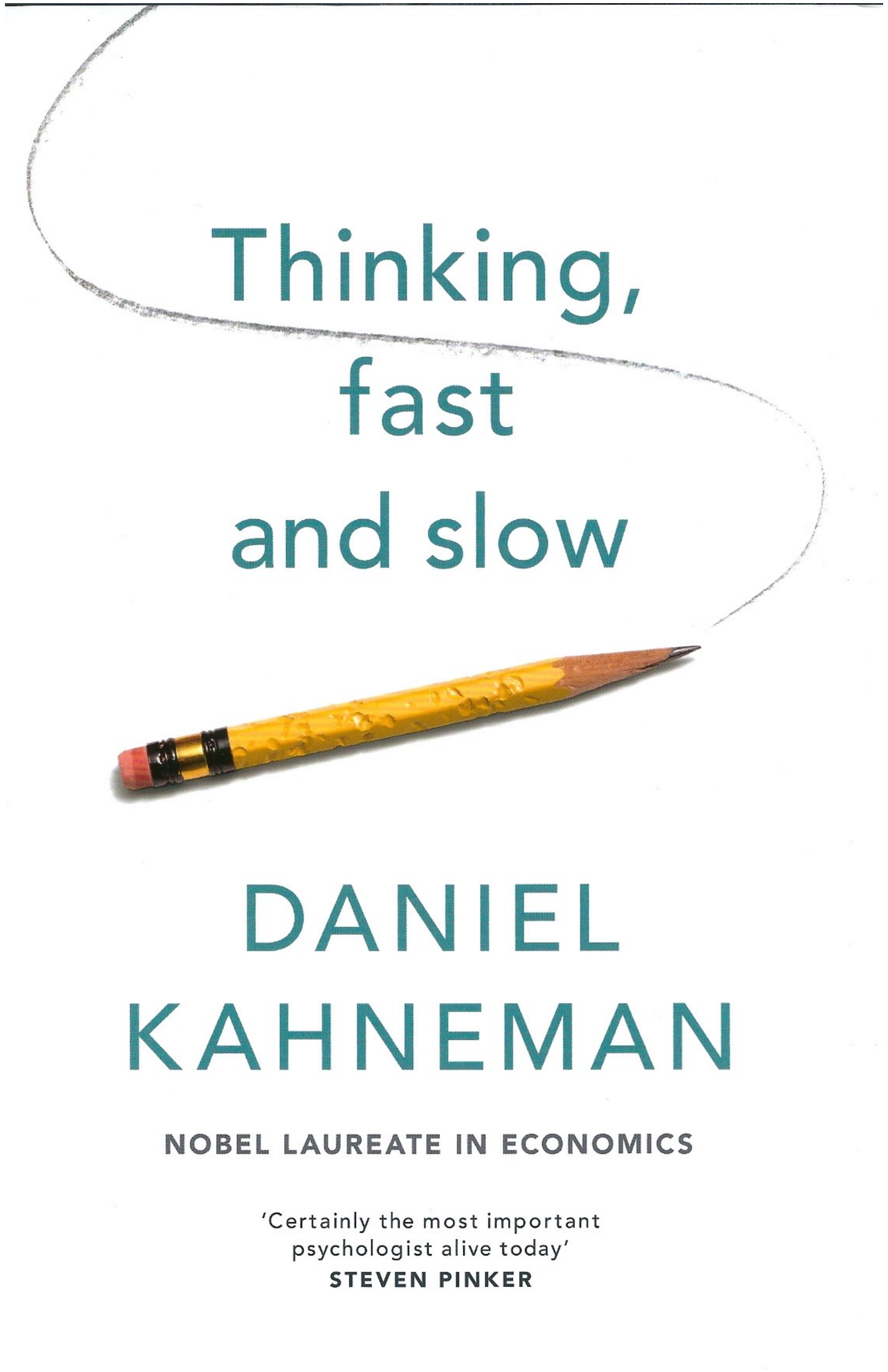
UZ LEUVEN

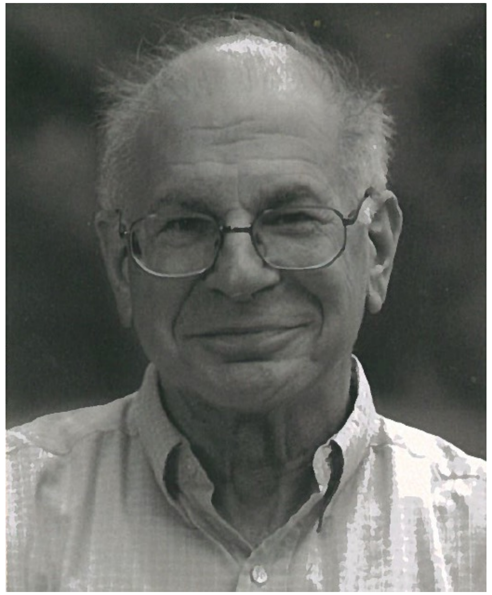


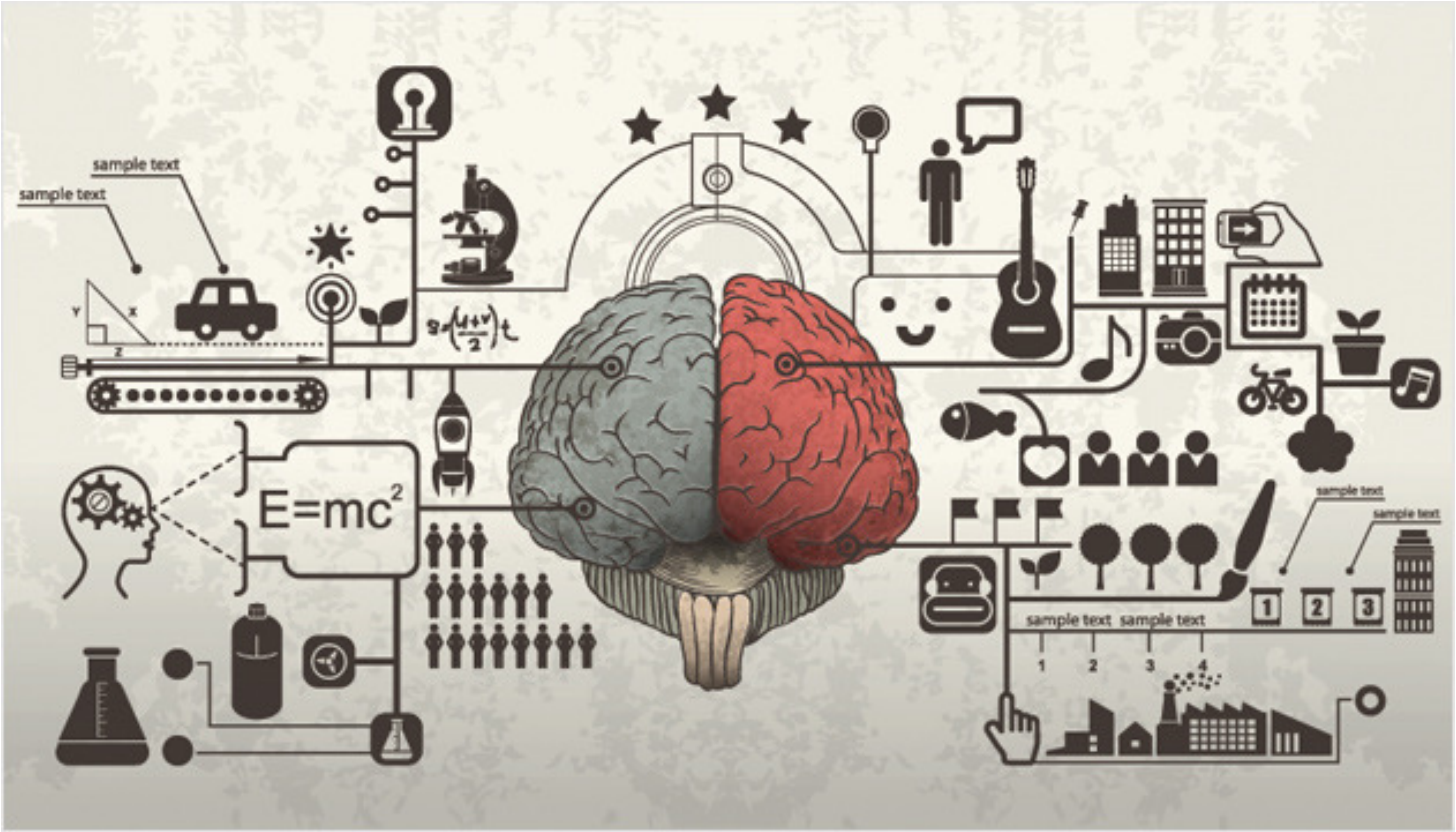
Frank E. Rademakers

Content

- Background and definitions
- What to expect
- What not to expect
- Impact on the Pharmacy
- Conclusions


Thinking, fast and slow
DANIEL KAHNEMAN
NOBEL LAUREATE IN ECONOMICS
'Certainly the most important psychologist alive today'
STEVEN PINKER

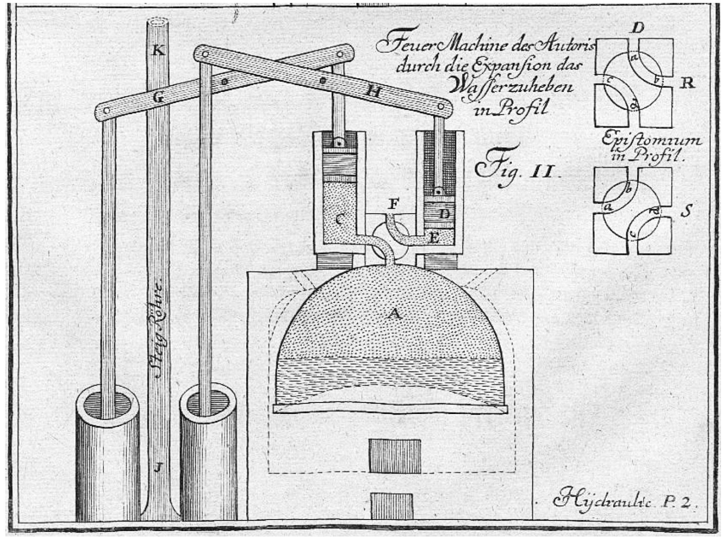




Learning and Reasoning

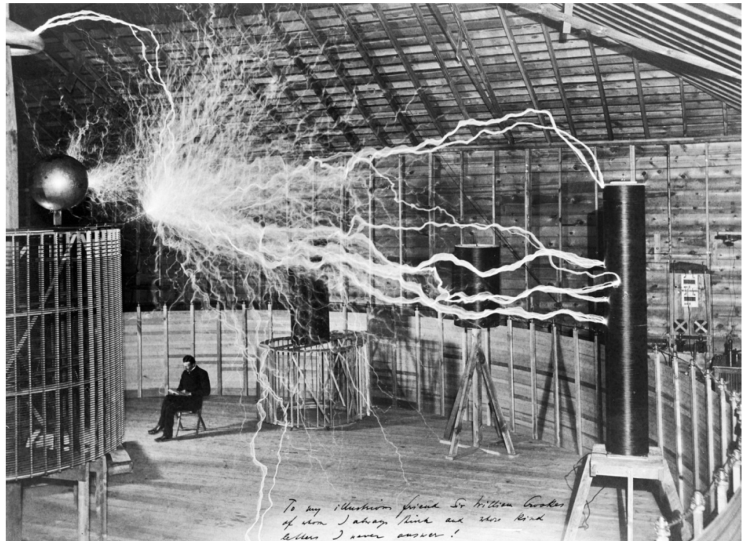
Four industrial revolutions

FIRST
Water and steam power mechanize production.



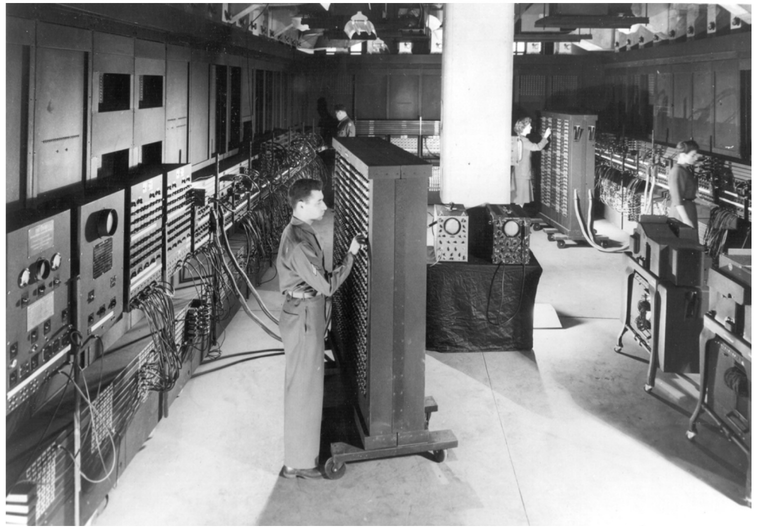
Four industrial revolutions

SECOND
Electric power creates mass production.



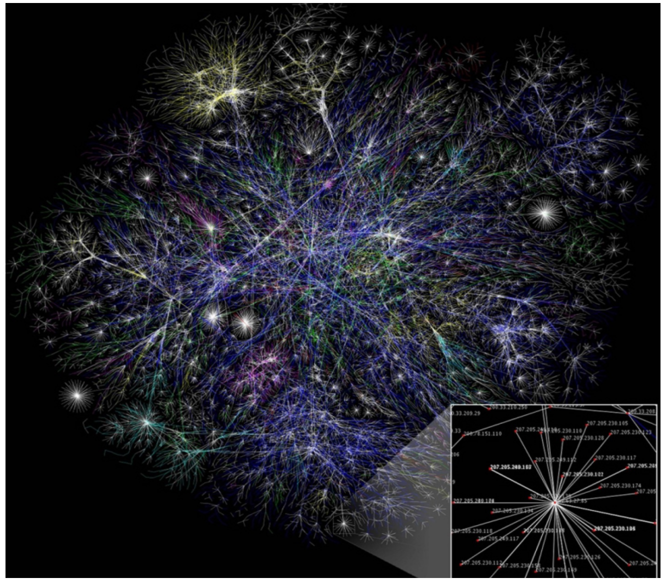
Four industrial revolutions

THIRD
Electronics and information technology automate production.



Four industrial revolutions

FOURTH
The digital revolution—characterized by a fusion of technologies—blurs the lines between physical, digital, and biological spheres.



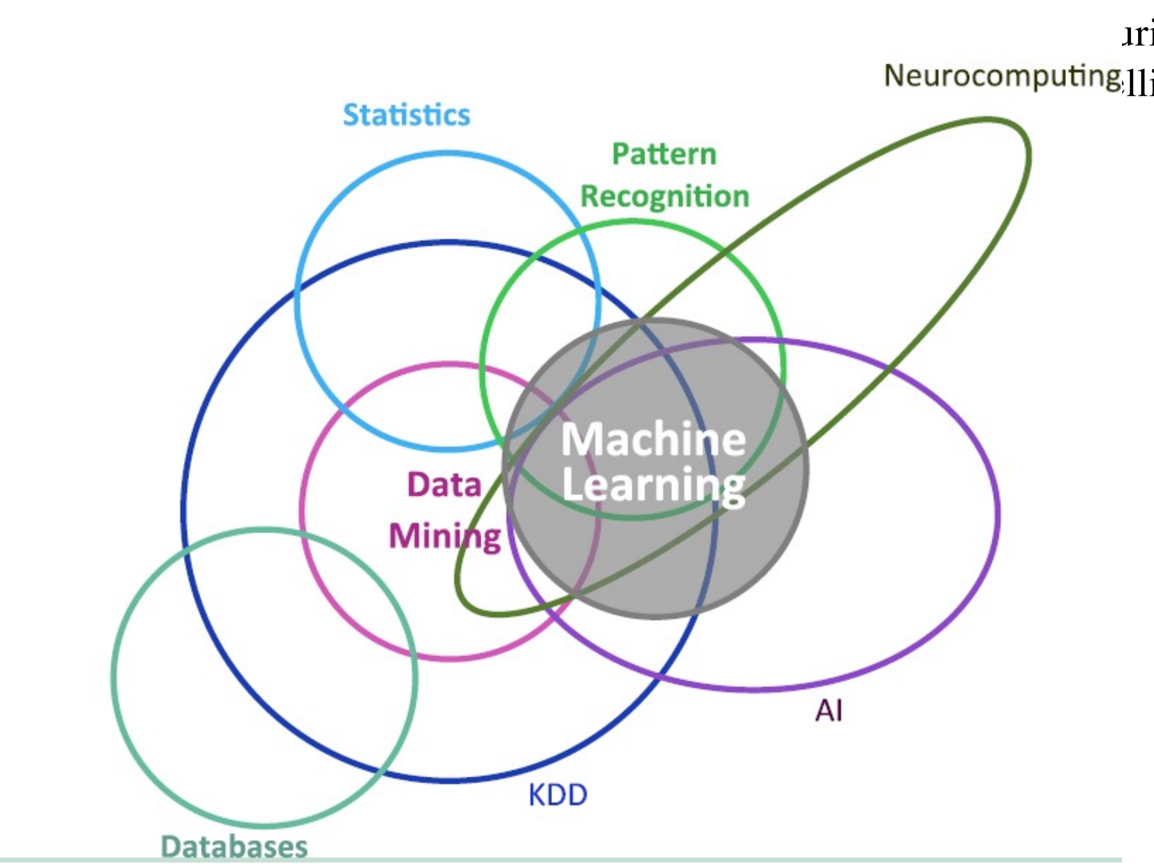
Artificial Intelligence in Medical Practice: The Question to the Answer?

D. Douglas Miller, MD, CM FACP,[a] Eric W. Brown, PhD[b]

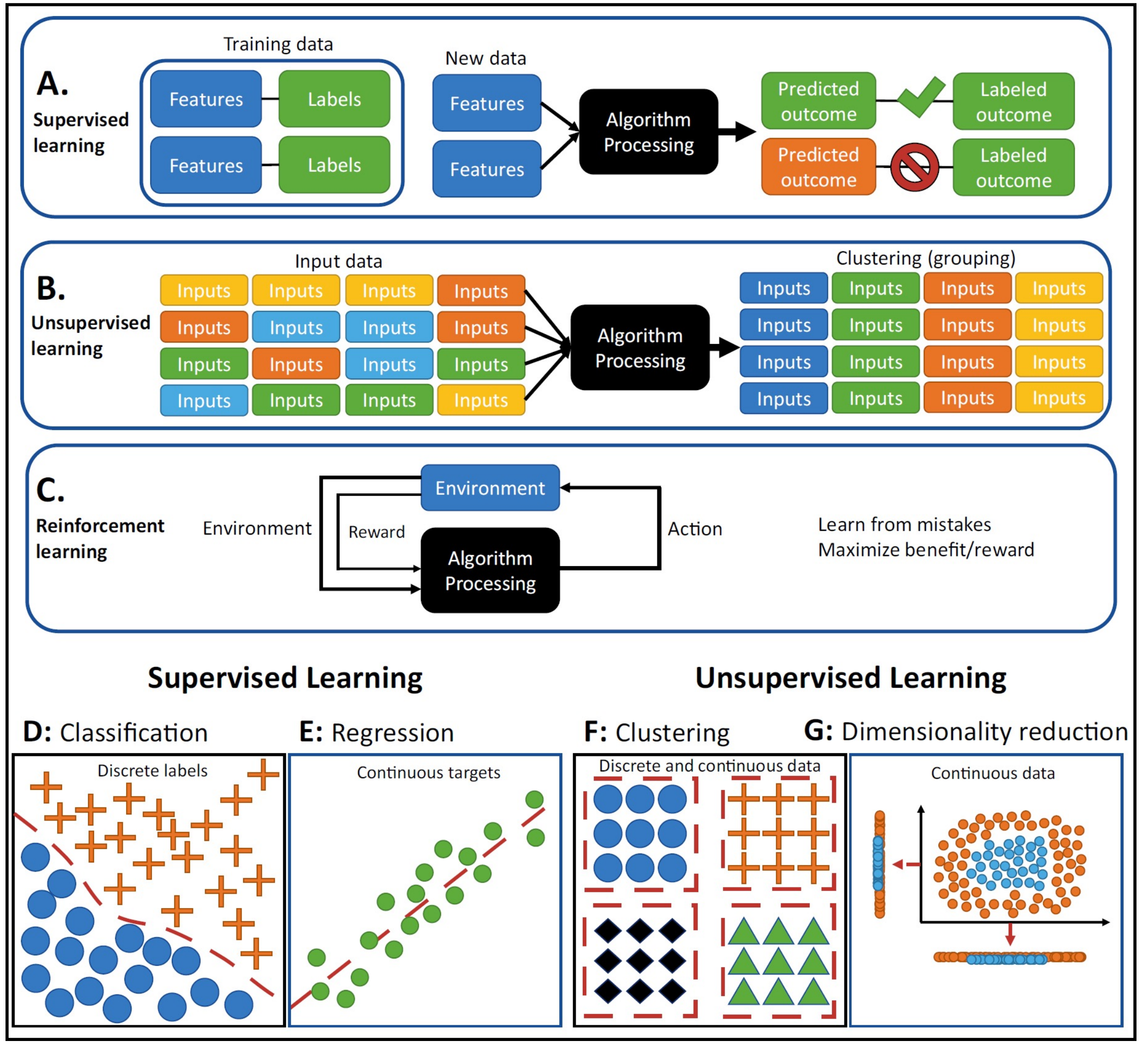
[a]New York Medical College, Valhalla; [b]Foundational Innovations, IBM Watson Health, Yorktown Heights, NY.

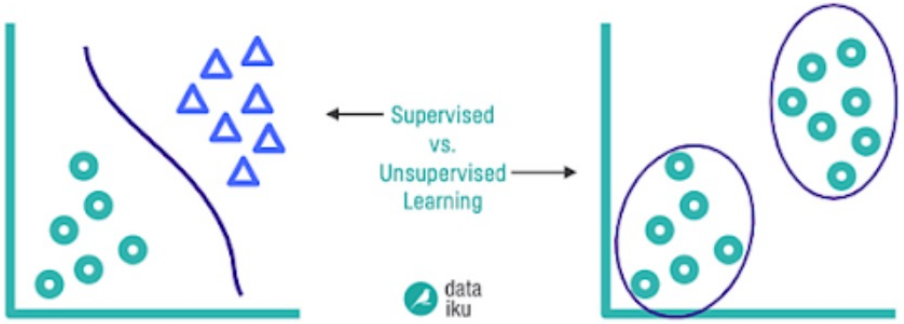
THE AI UNIVERSE

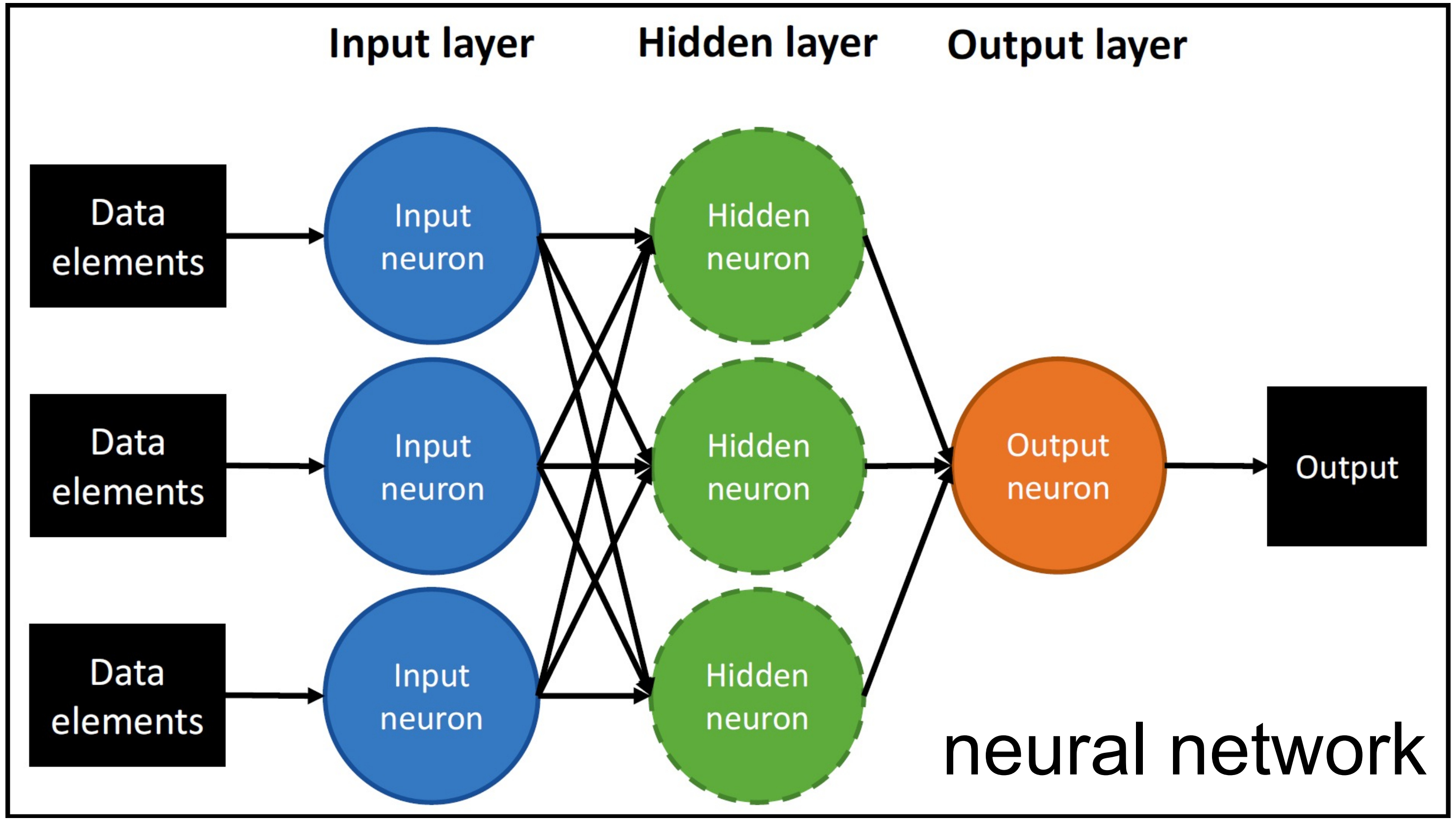
mbers, With an Application to the Entscheidungsproblem, '[1] Turing's life was reprised in the 2014 film, ***The*** ıring and his Princeton colleague, Alonzo Church, used :lligent human problemsolving became the basis of

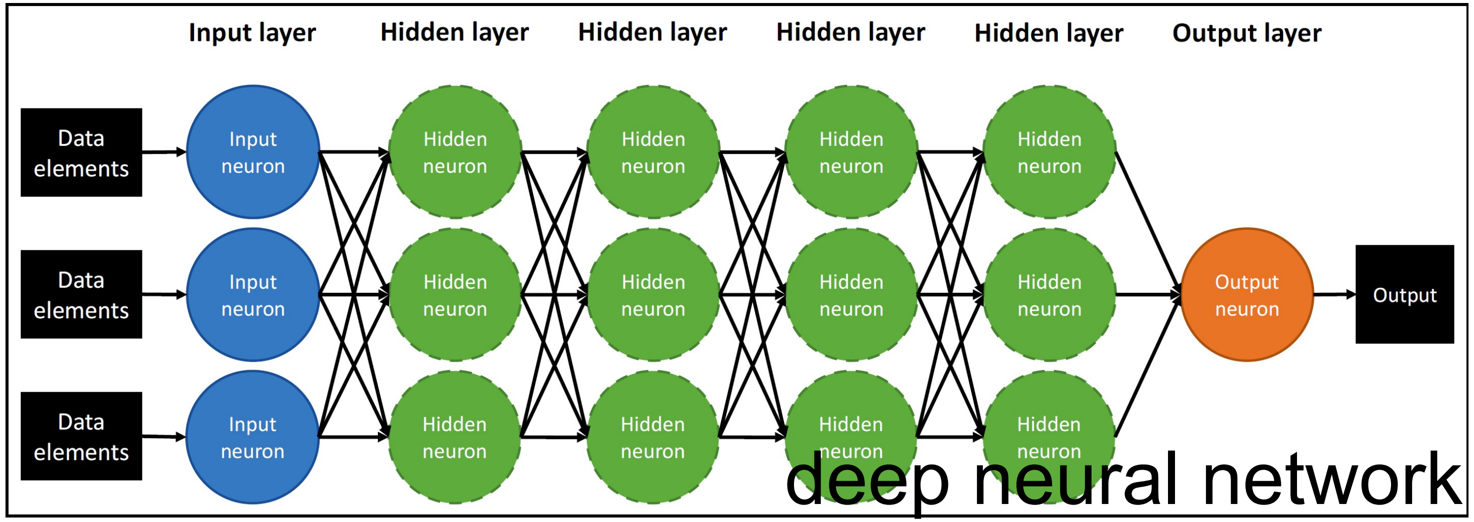


The American Journal of Medicine (2018) 131, 129–133



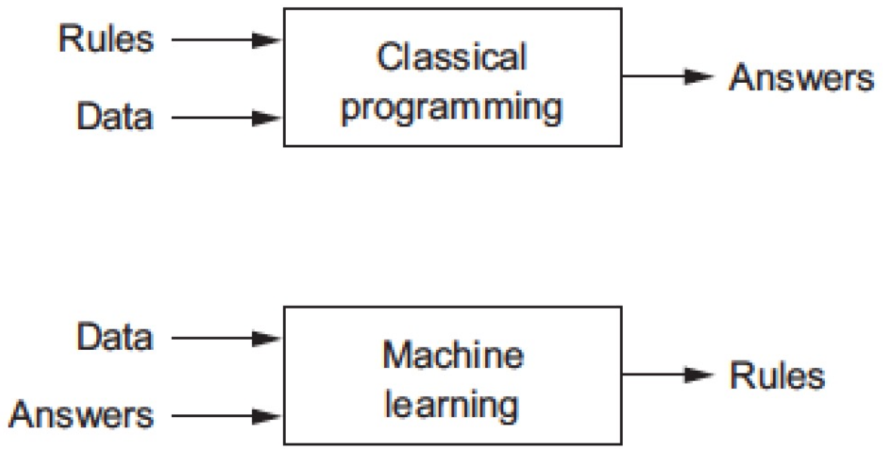


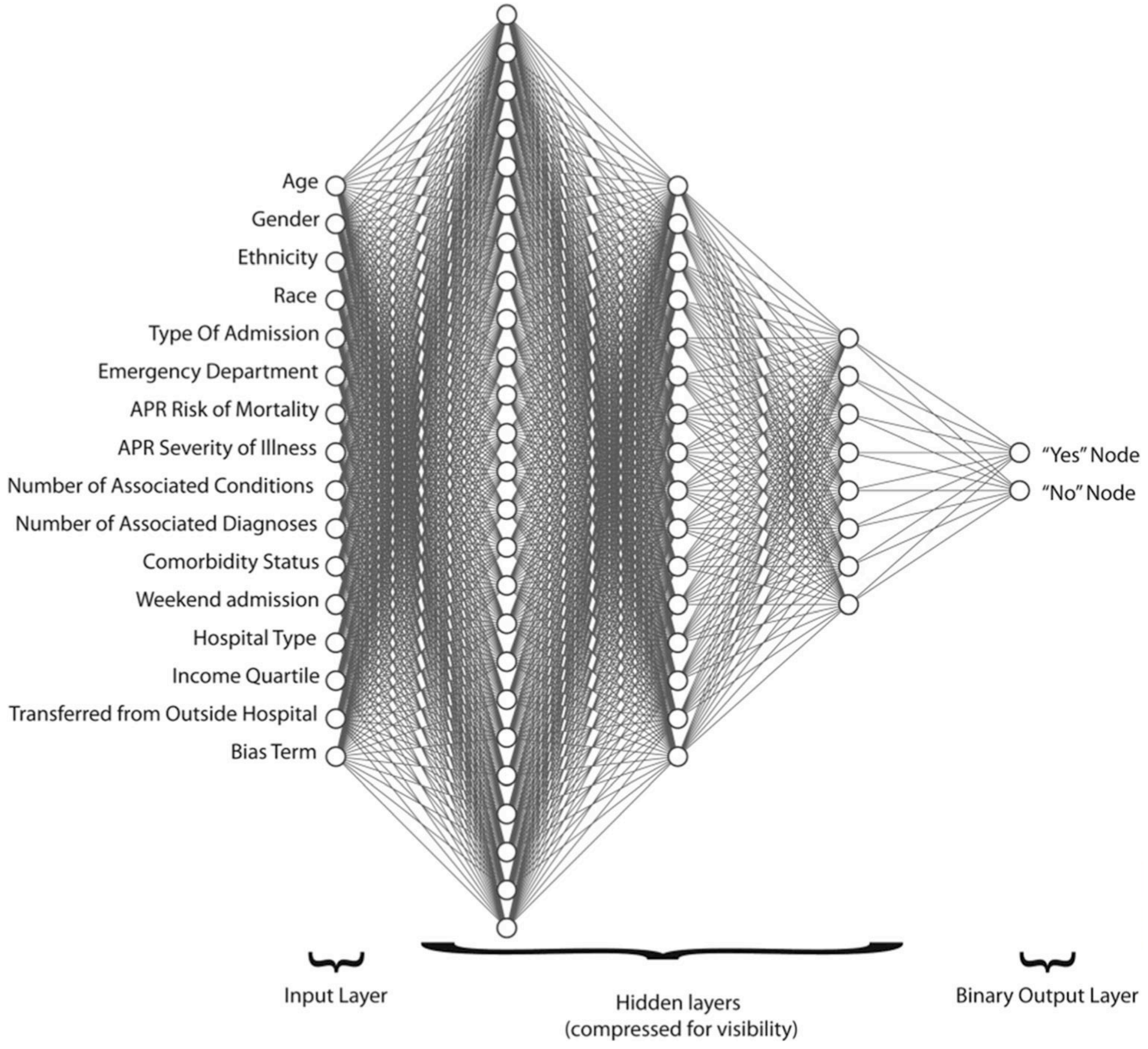




AM J HEALTH-SYST PHARM | VOLUME 77 | NUMBER 19 | OCTOBER 1, 2020

Machine learning – Deep learning

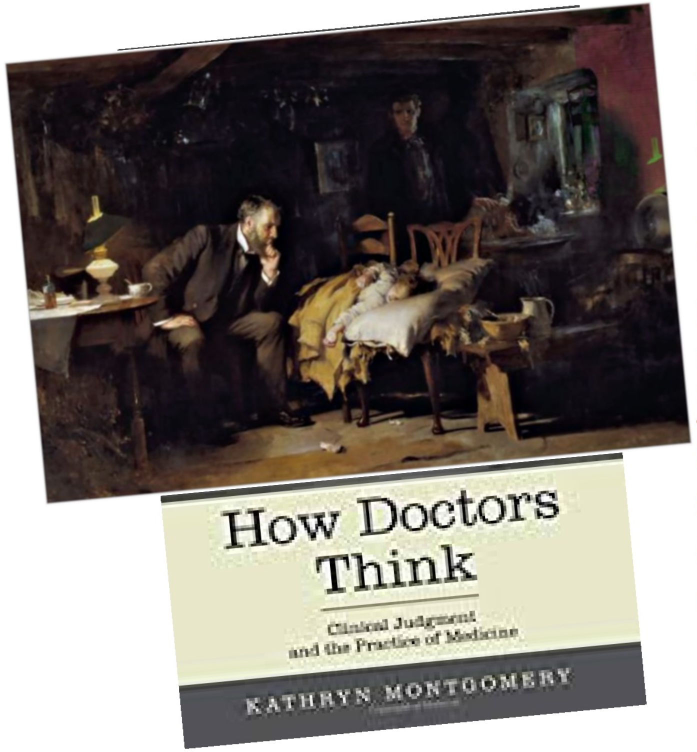




AI = the use of computer systems
to analyze large quantities of data, then
applying the results of those analyses
programmatically to better inform decisions.

Explainability

AI Shifts Emphasis from Traditional Clinical Judgment to Data Science



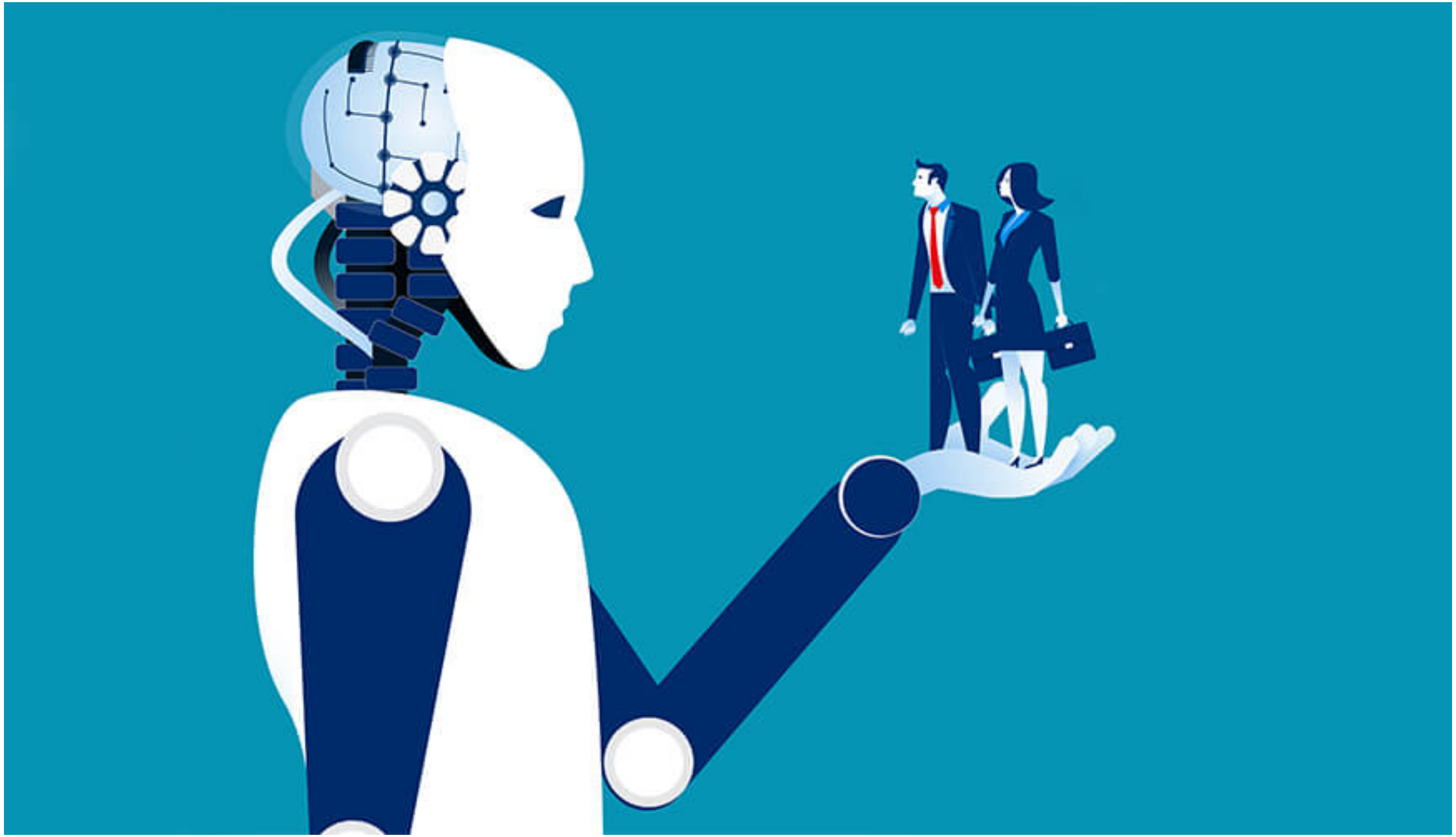
Linear, Logical & Sequential Thinking!

Traditionally a physician looks at the patient's history along with the presenting physical signs and symptoms and juxtaposes these with clinical experience and empirical studies to construct a tentative account of the illness.

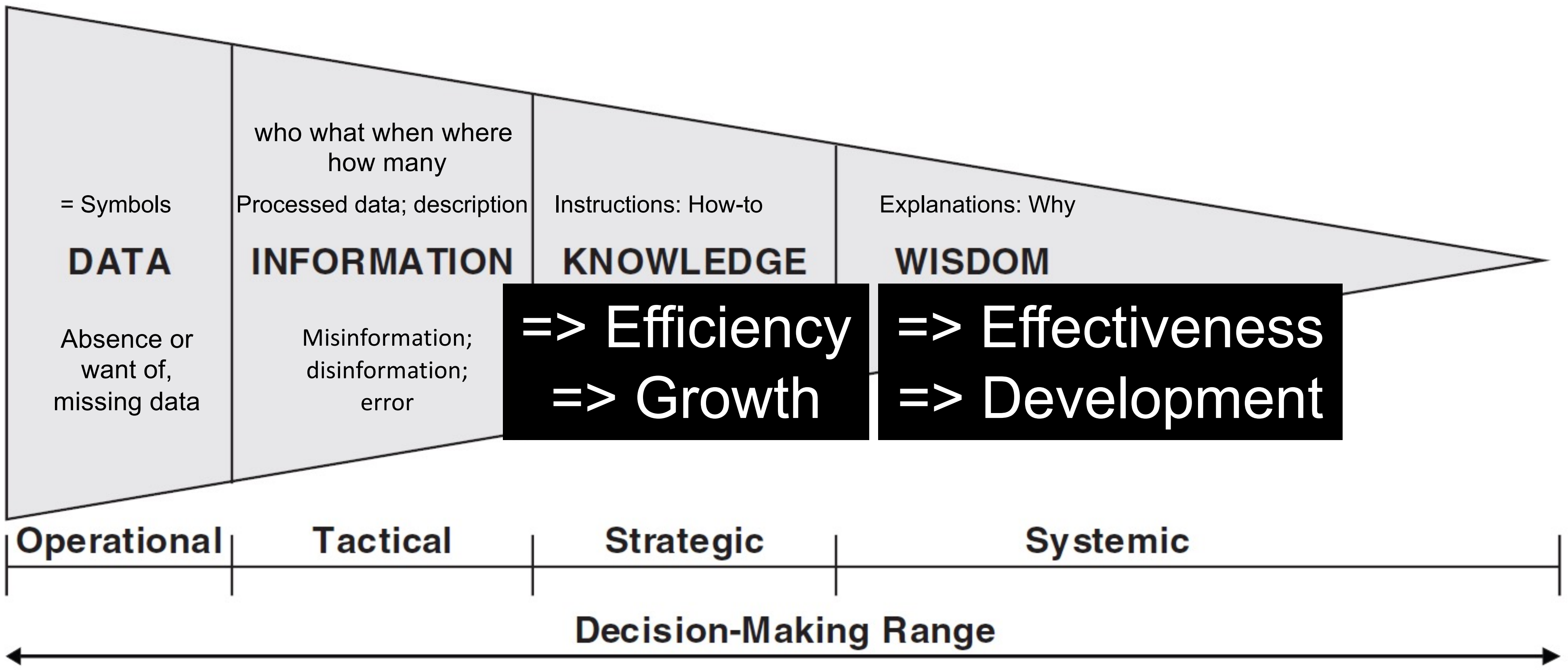
ORGANISMS = ALGORITHMS

Harari Homo Deus

Threat or Opportunity



Decision-making framework



Evidence – based
Outcome driven

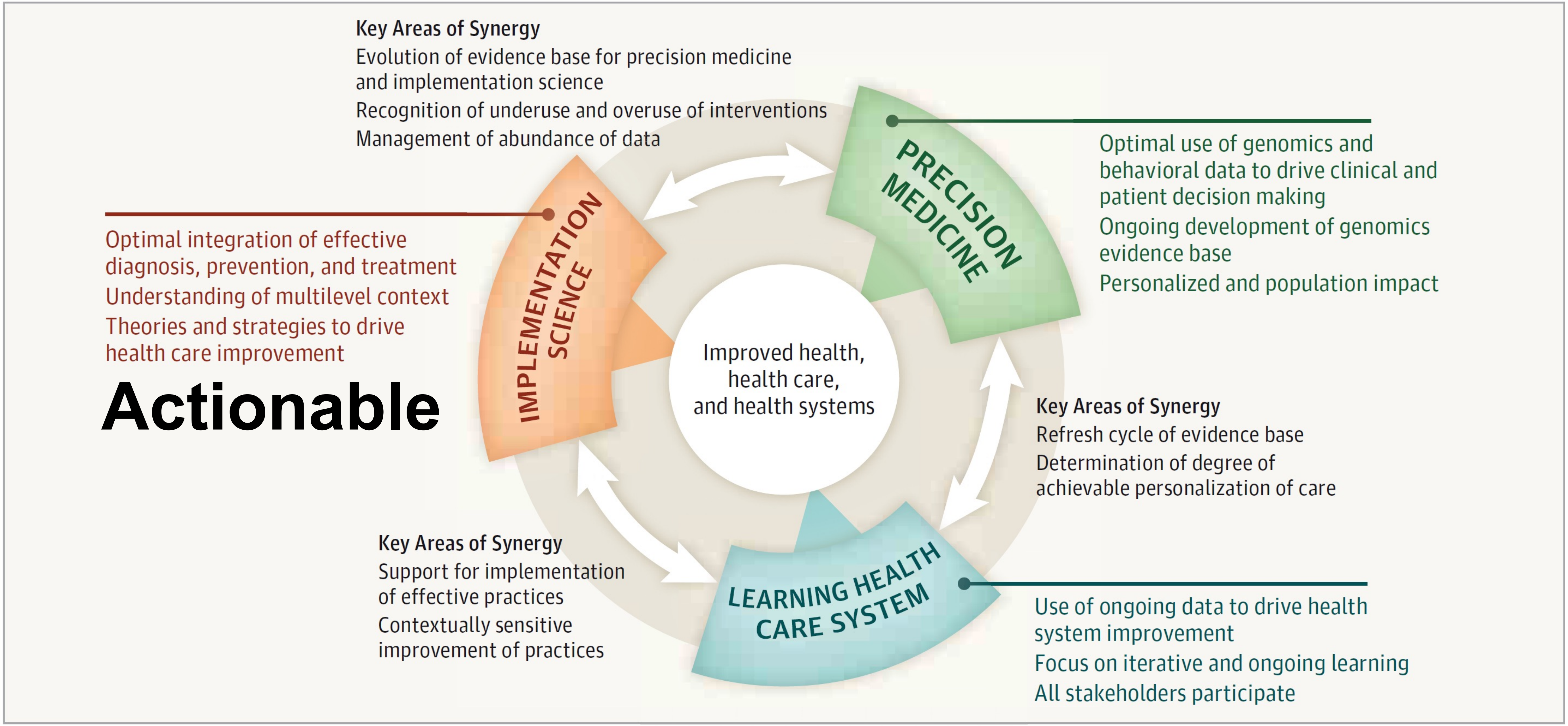
$$\textbf{VALUE} = \left(\frac{\textbf{QUALITY}}{\textbf{COST}}\right) \textbf{EXPERIENCE}$$

Determining Cost and
Stratifying the Risks

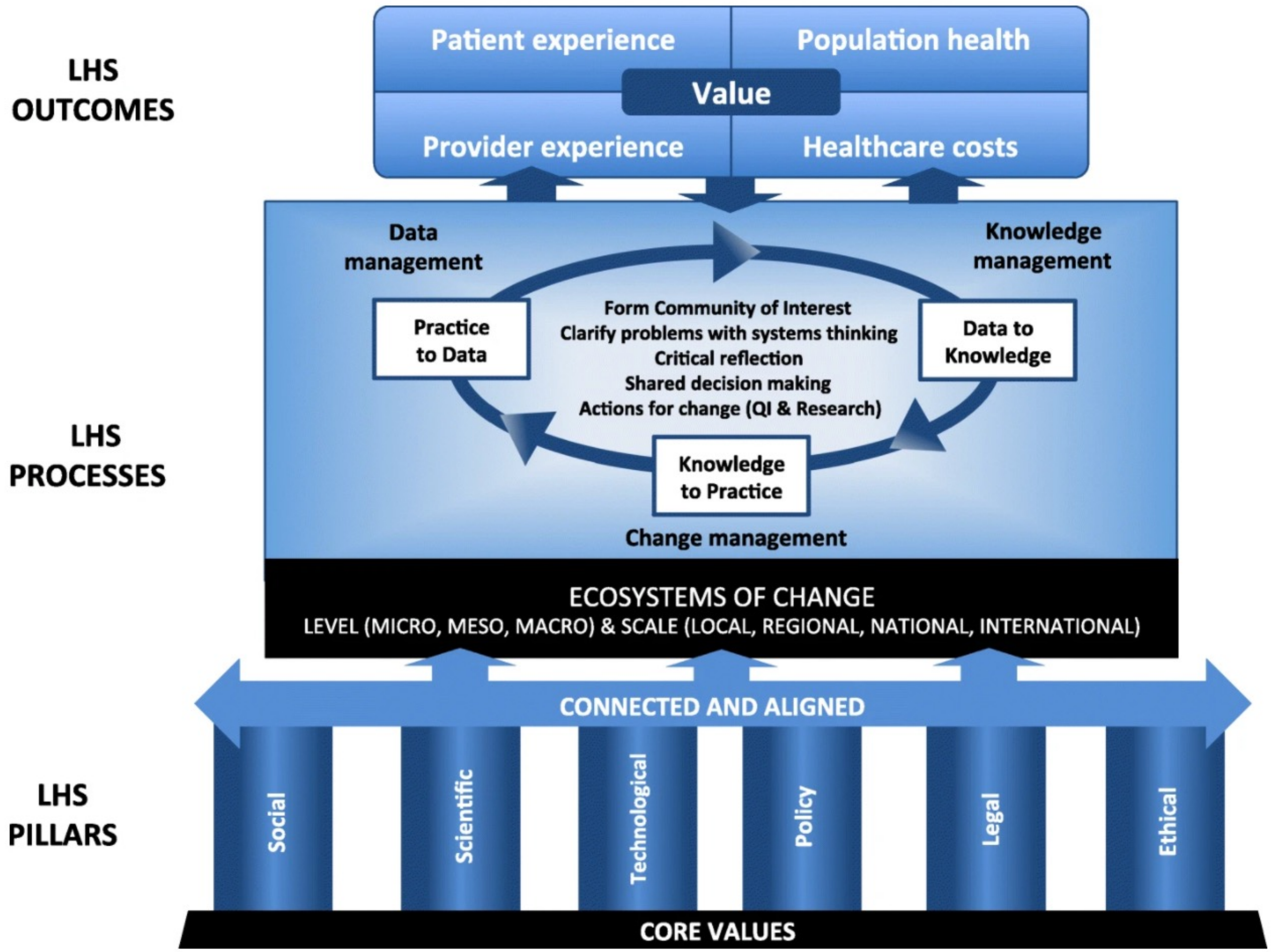
Longitudinal coordination and
communication

DATA supported

Figure. Contributions of Implementation Science, Learning Health Care System, and Precision Medicine



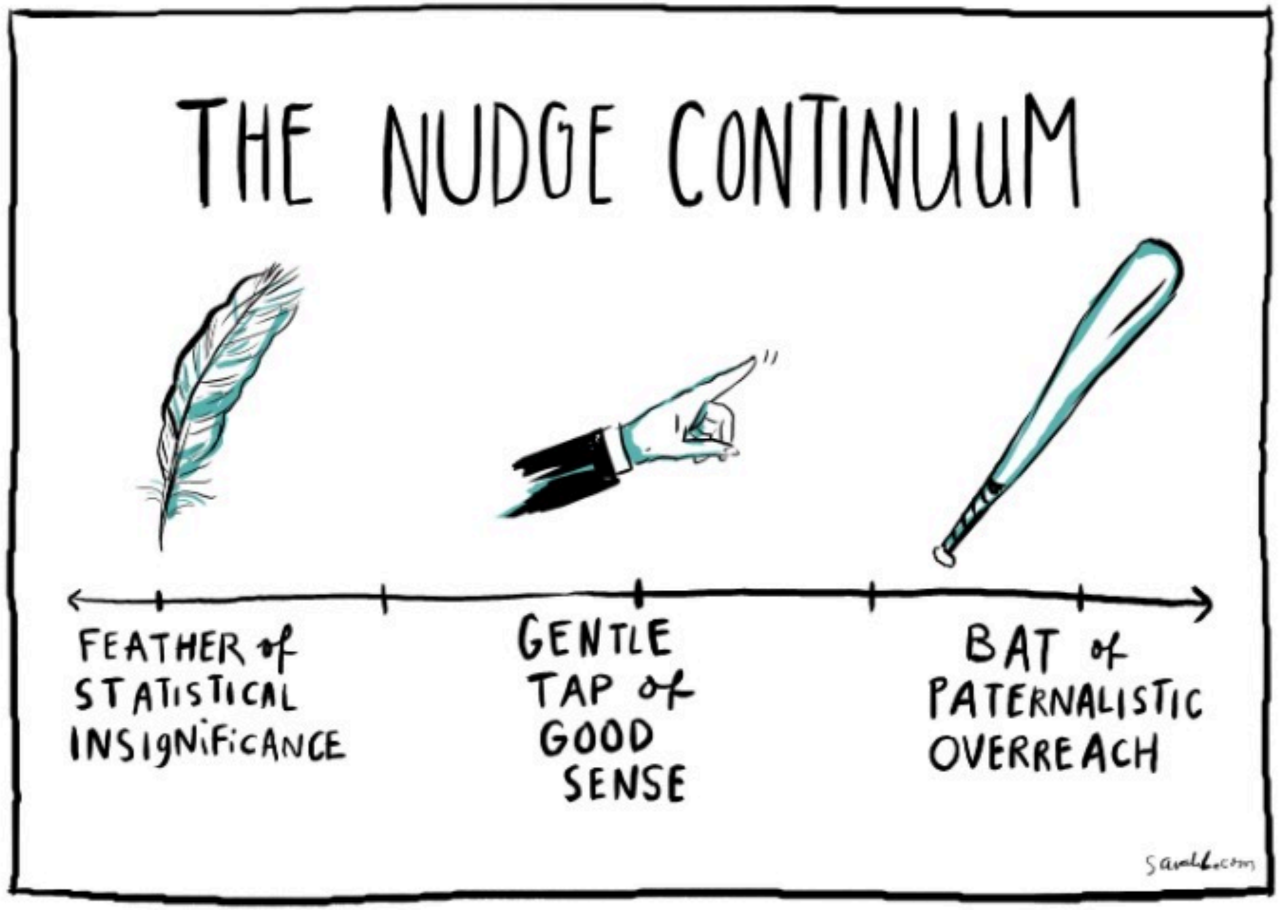
Actionable



Conceptual framework for value-creating learning health systems

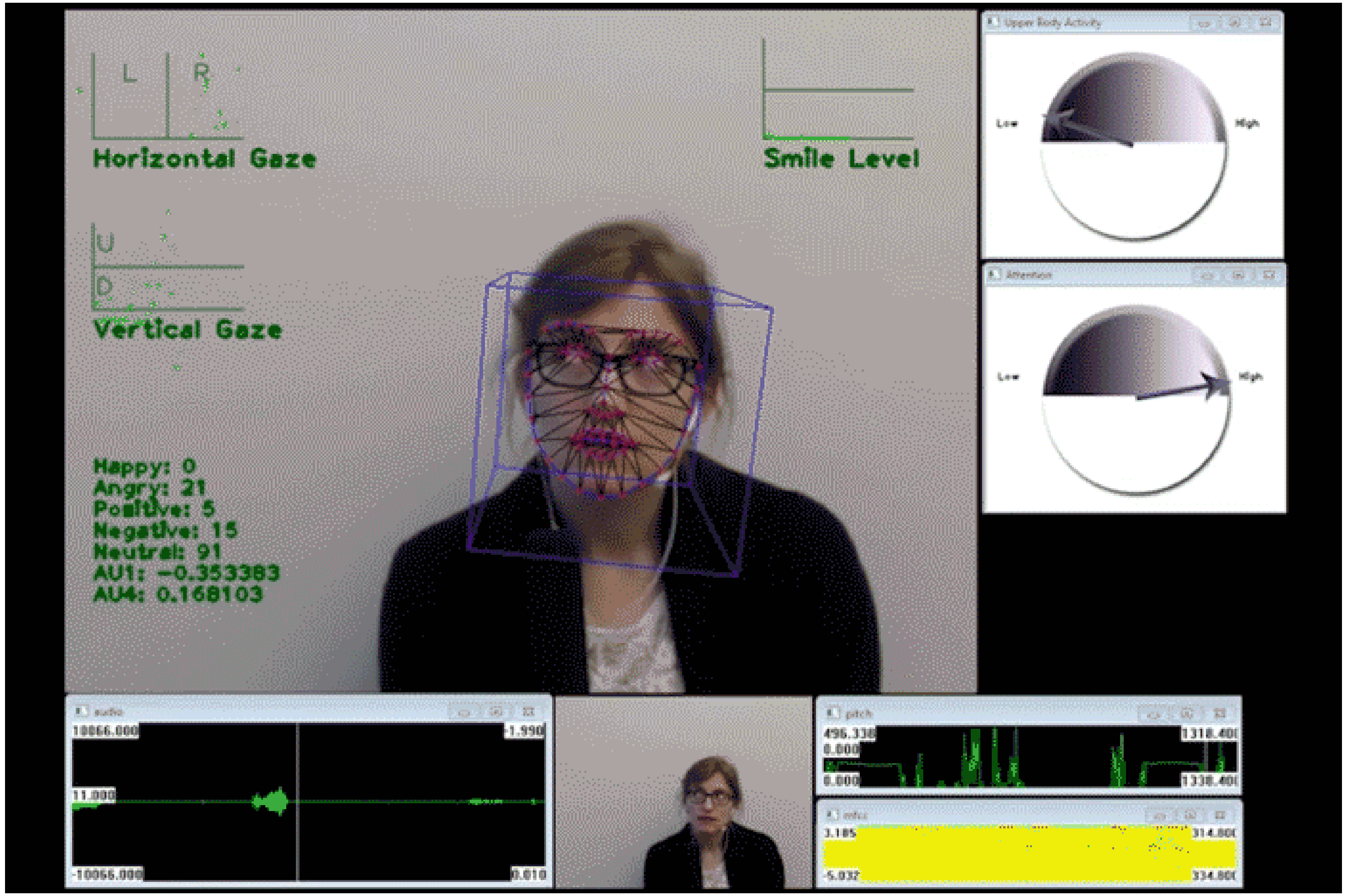
The Psychology of Clinical Decision Making — Implications for Medication Use

Jerry Avorn, M.D.



n engl j med 378;8 nejm.org February 22, 2018

Cure in a virtual reality

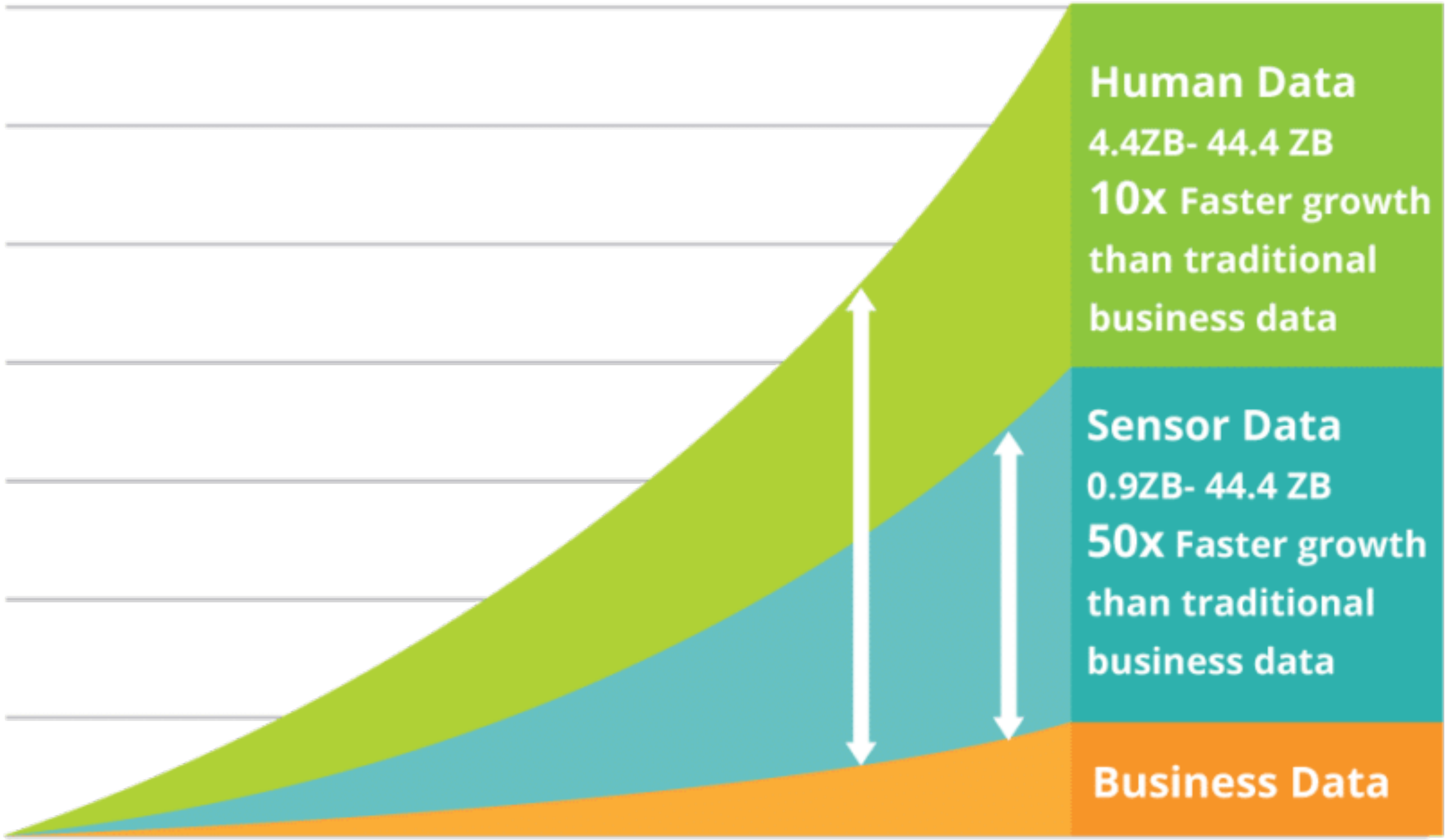


Her name is Ellie. She introduces herself in a calm voice. Ellie is an avatar, designed to interview mental health patients, gather information about their symptoms and help doctors to develop a diagnosis.

https://mindthehorizon.com/2015/09/21/avatar-virtual-reality-mental-health-tech/

The growth of human and machine-generated data

Hu

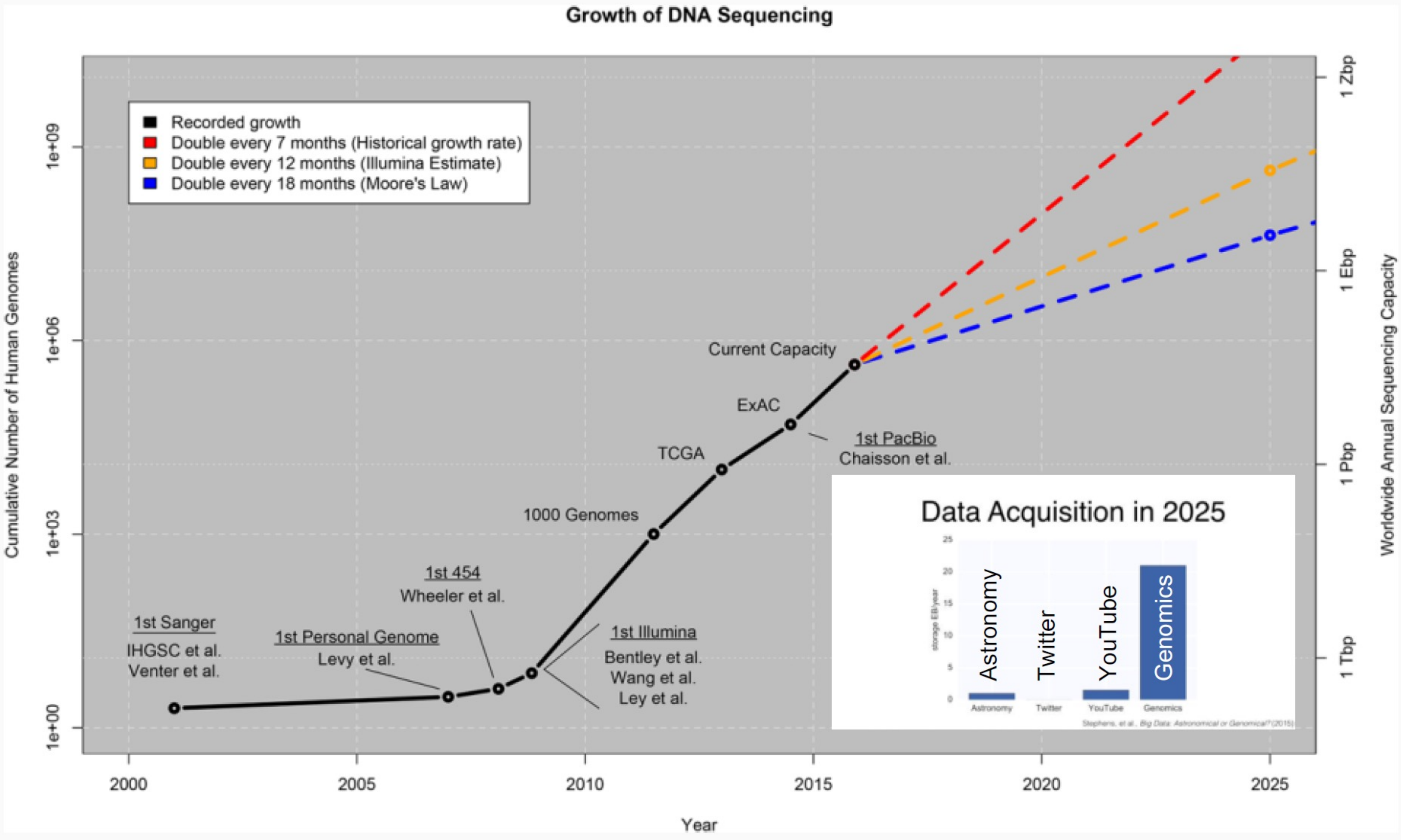


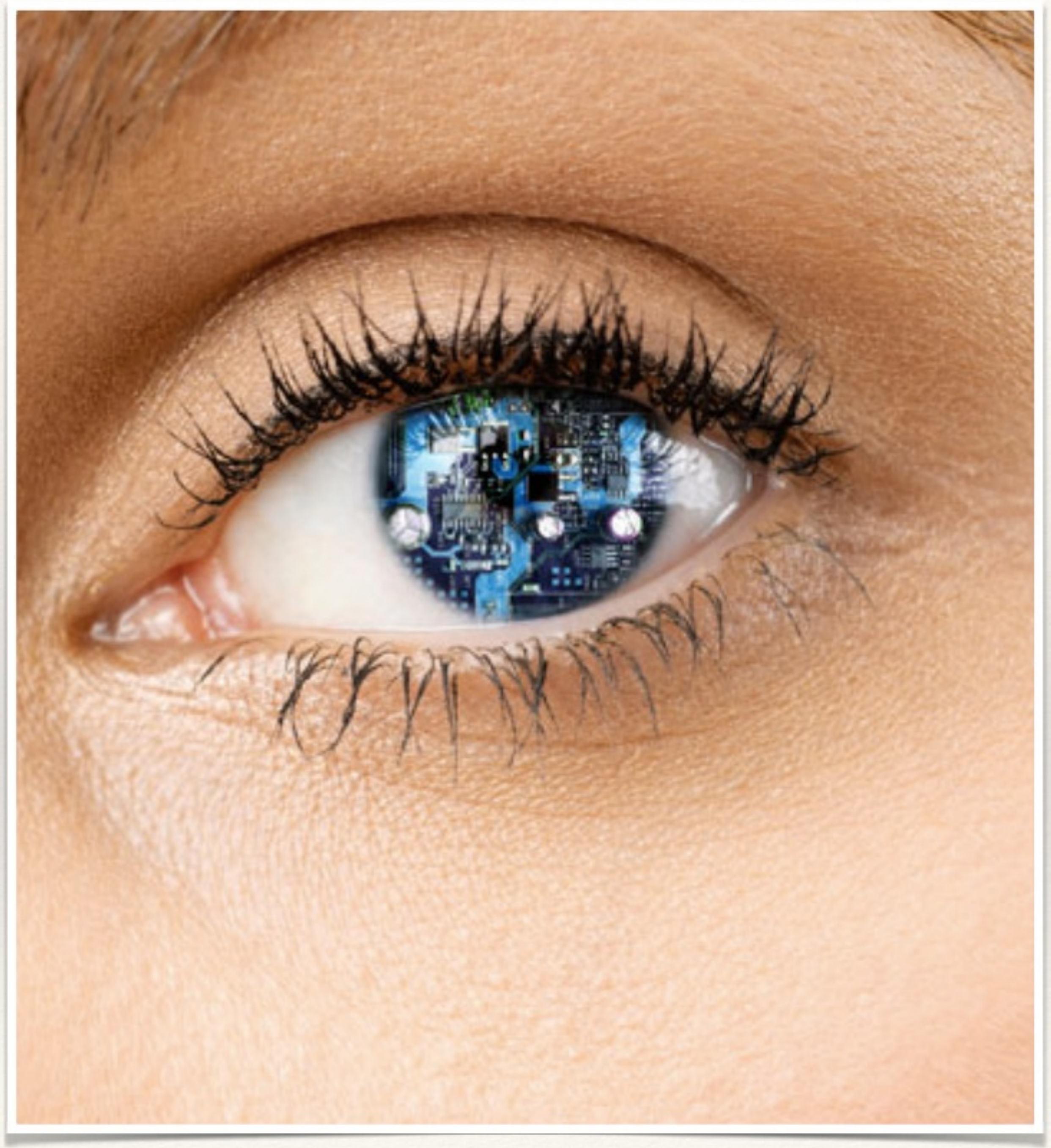
les

ɔhenotype

Source: Inside big data

Genomics will outpace other BigData disciplines



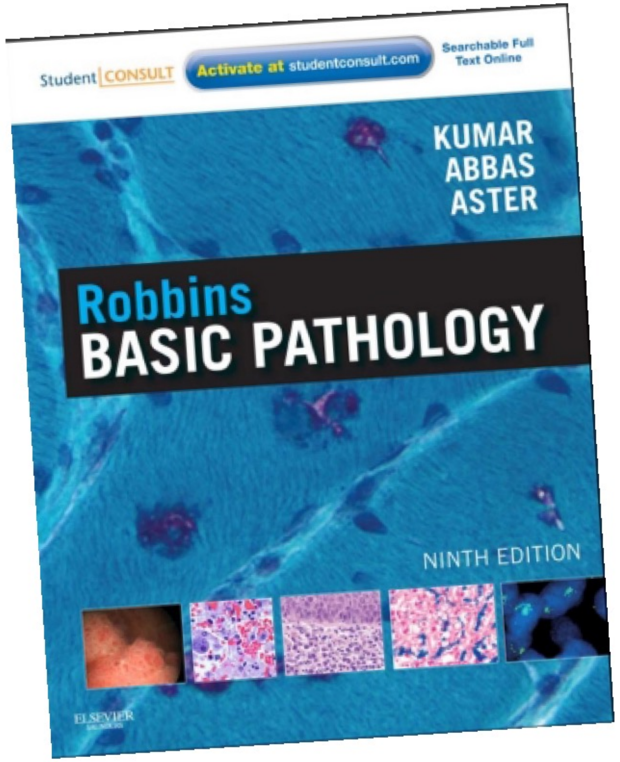


‘insideables’

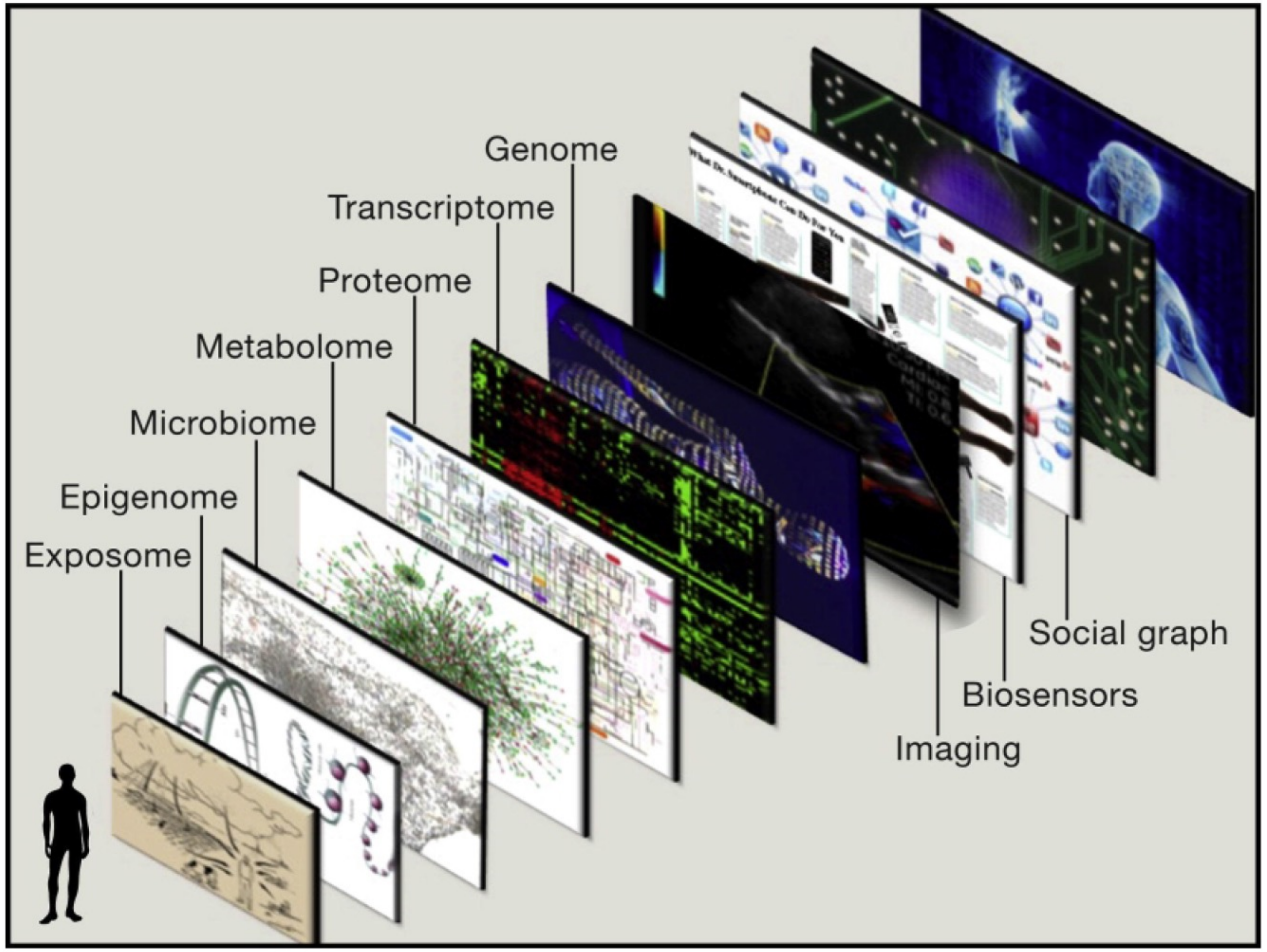

hybrid
hybridmedicalanimation.com

Role of mHealth: New Taxonomy of Disease

1988



2017



Topol EJ. Individualized medicine from prewomb to tomb. Cell 2014;241-53

Content

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- What not to expect
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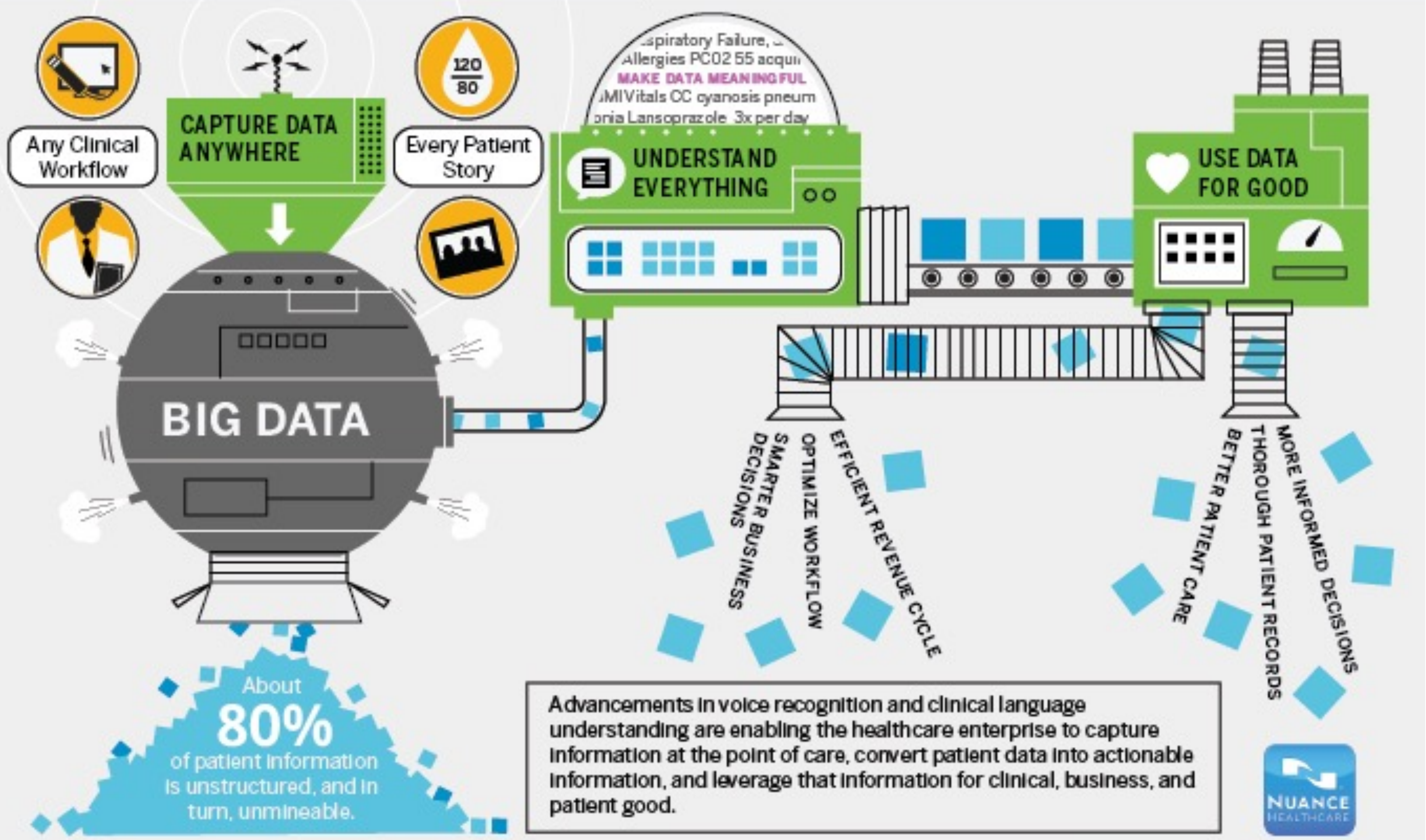
HEALTHCARE'S DATA CONUNDRUM

FROM DISPARATE DATA TO MEANINGFUL INFORMATION

We can empower healthcare organizations, providers and payers to unify the capture, analysis, and use of data to drive smarter care and business.



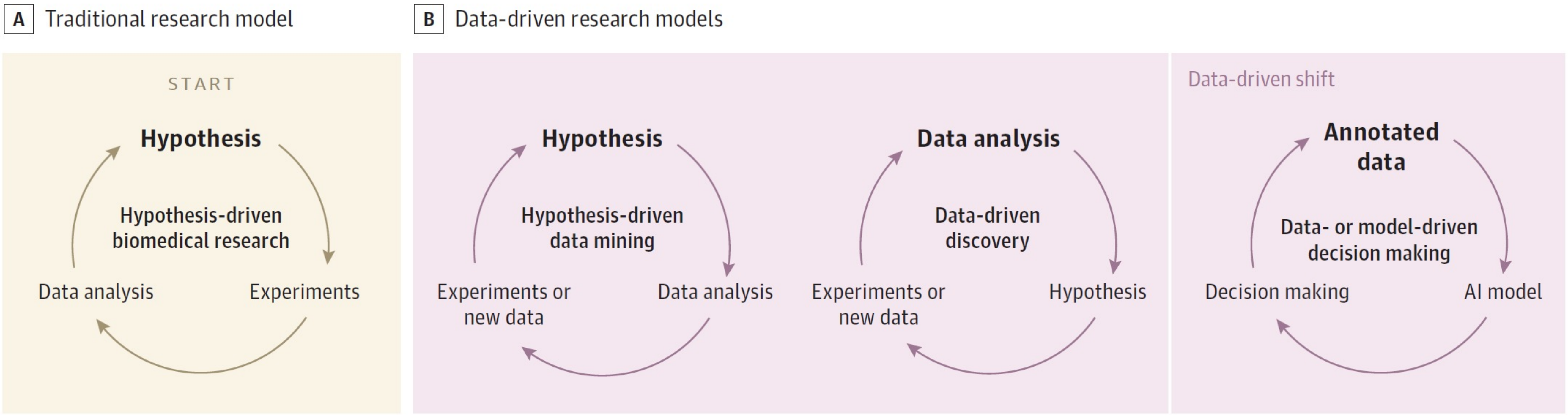
Advancements in voice recognition and clinical language understanding are enabling the healthcare enterprise to capture information at the point of care, convert patient data into actionable information, and leverage that information for clinical, business, and patient good.

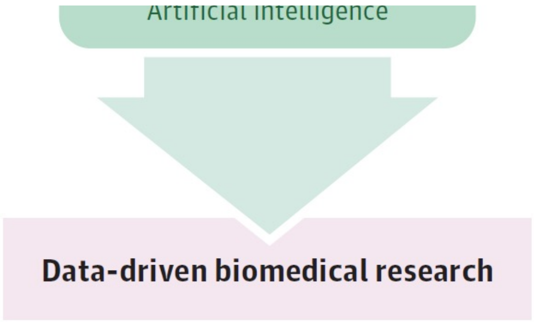
NUANCE HEALTHCARE

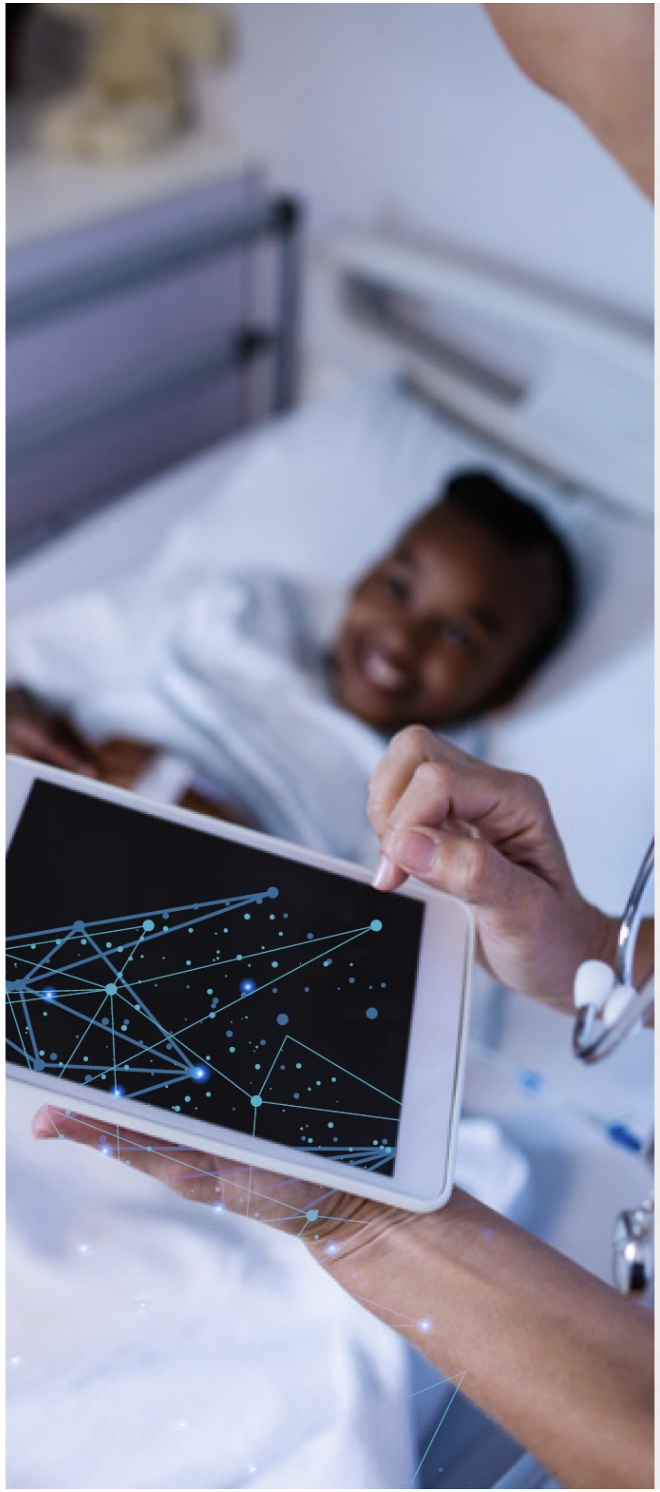
www.nuance.com/for-healthcare

Figure 1. Biomedical Research and Informatics Approaches in Artificial Intelligence

Figure 2. Traditional Research Model and Data-Driven Models in Artificial Intelligence







Technological advances impacting healthcare and the magnitude of disruption.

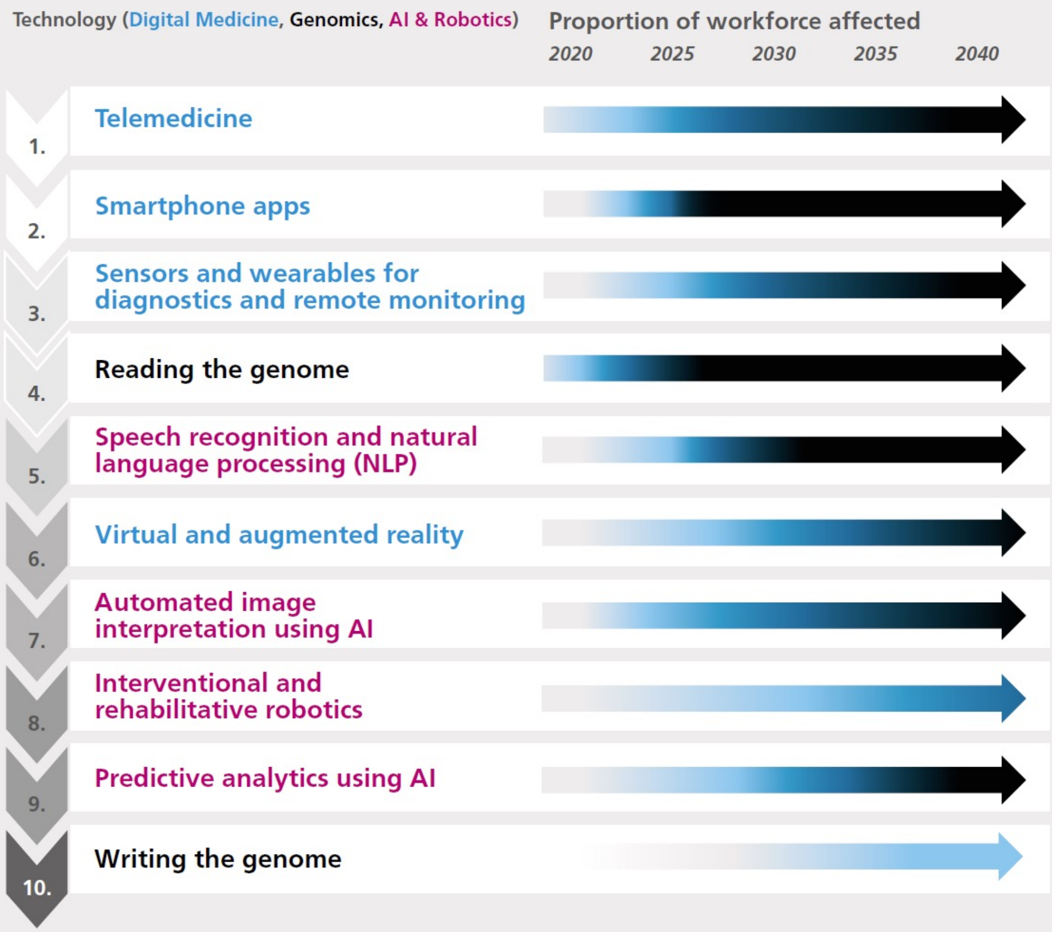
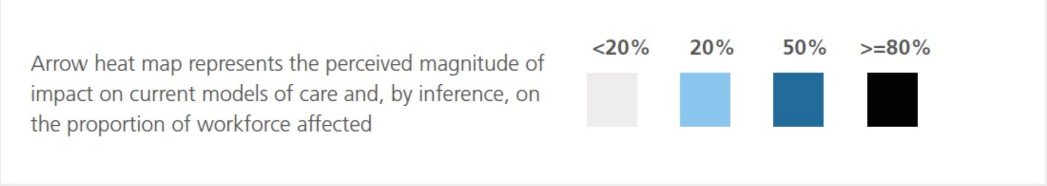
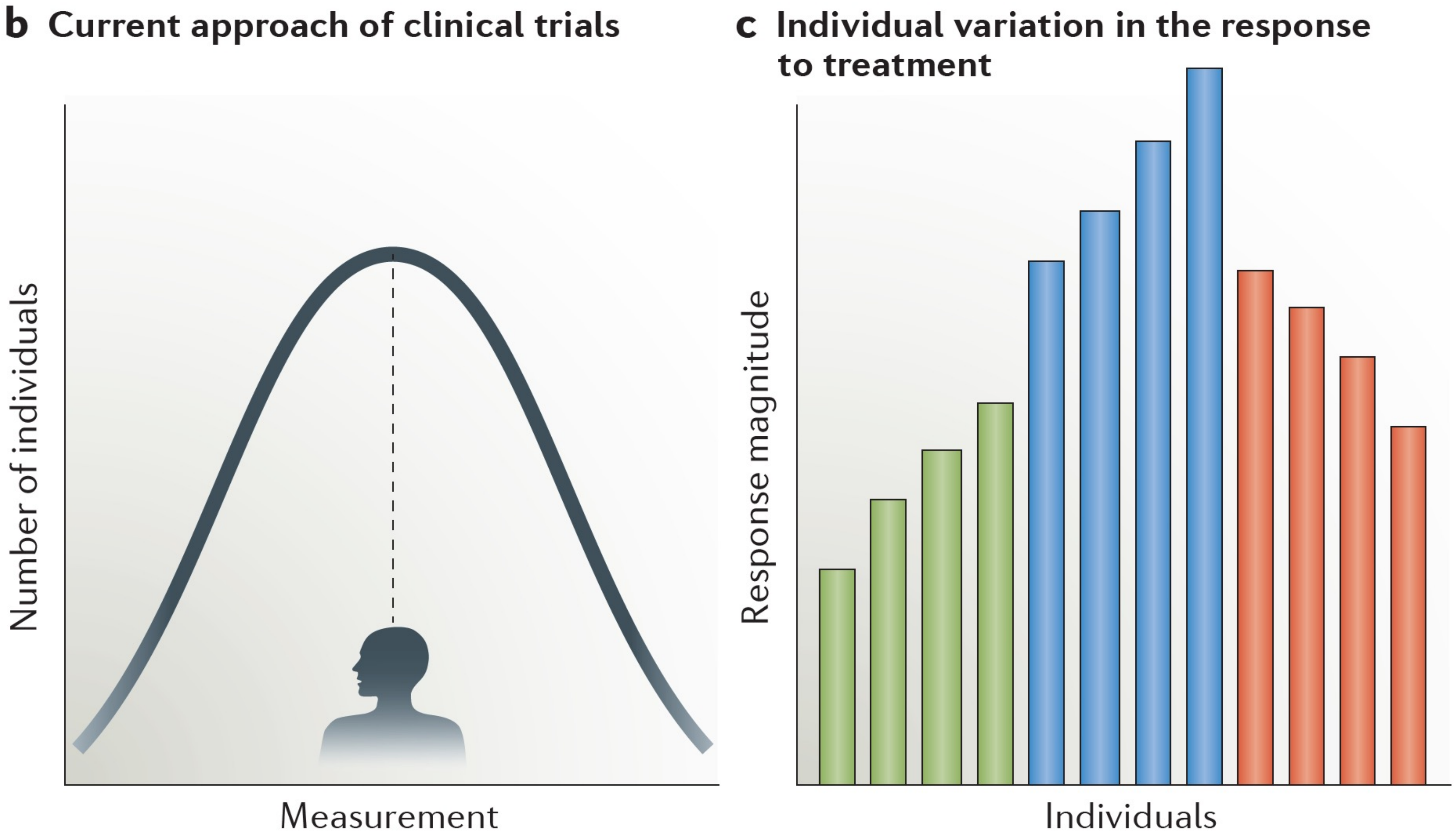


Figure 1: Top 10 digital healthcare technologies and their projected impact on the NHS workforce from 2020 to 2040



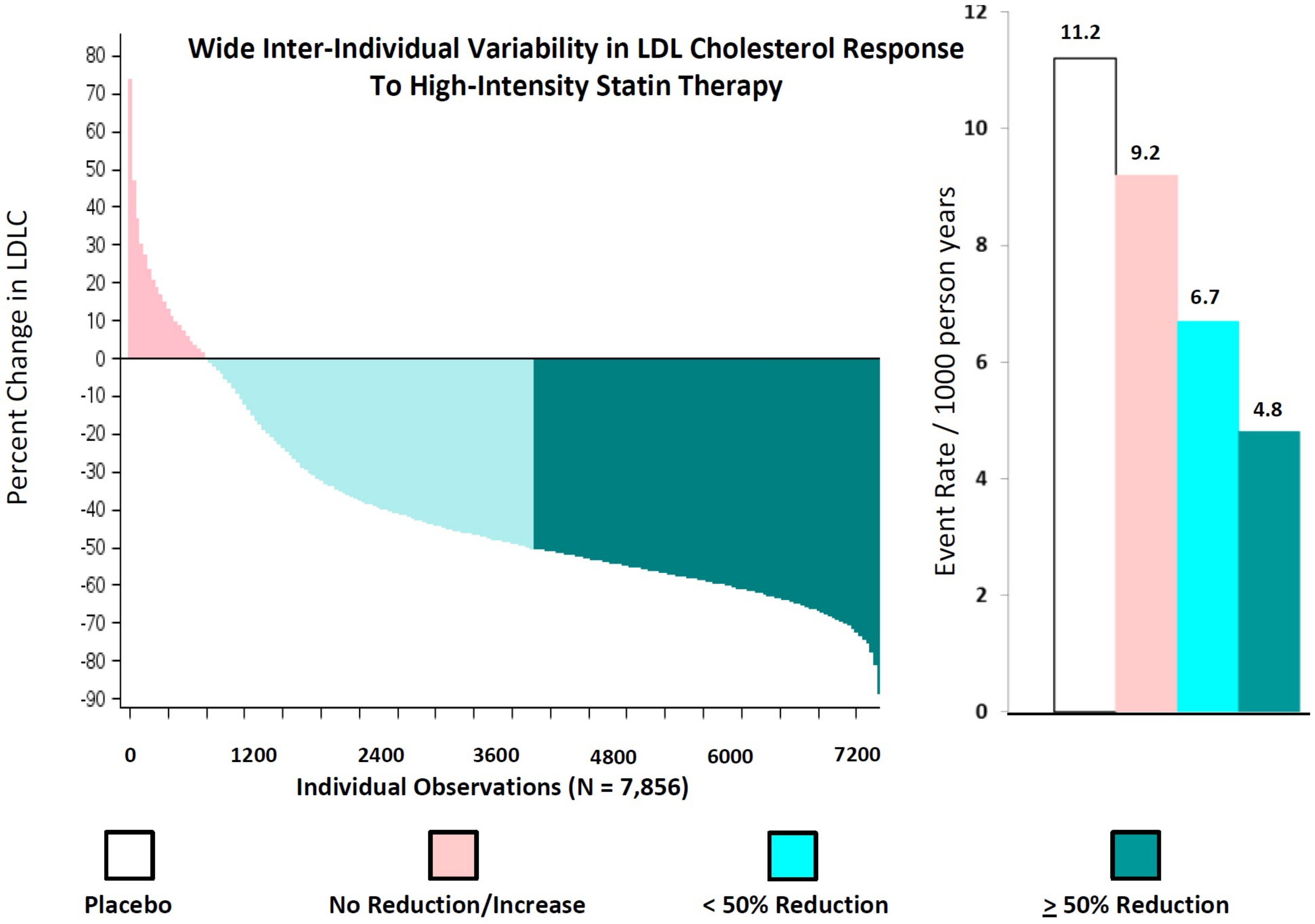
The problem of averaging population data

Biological continuum of disease

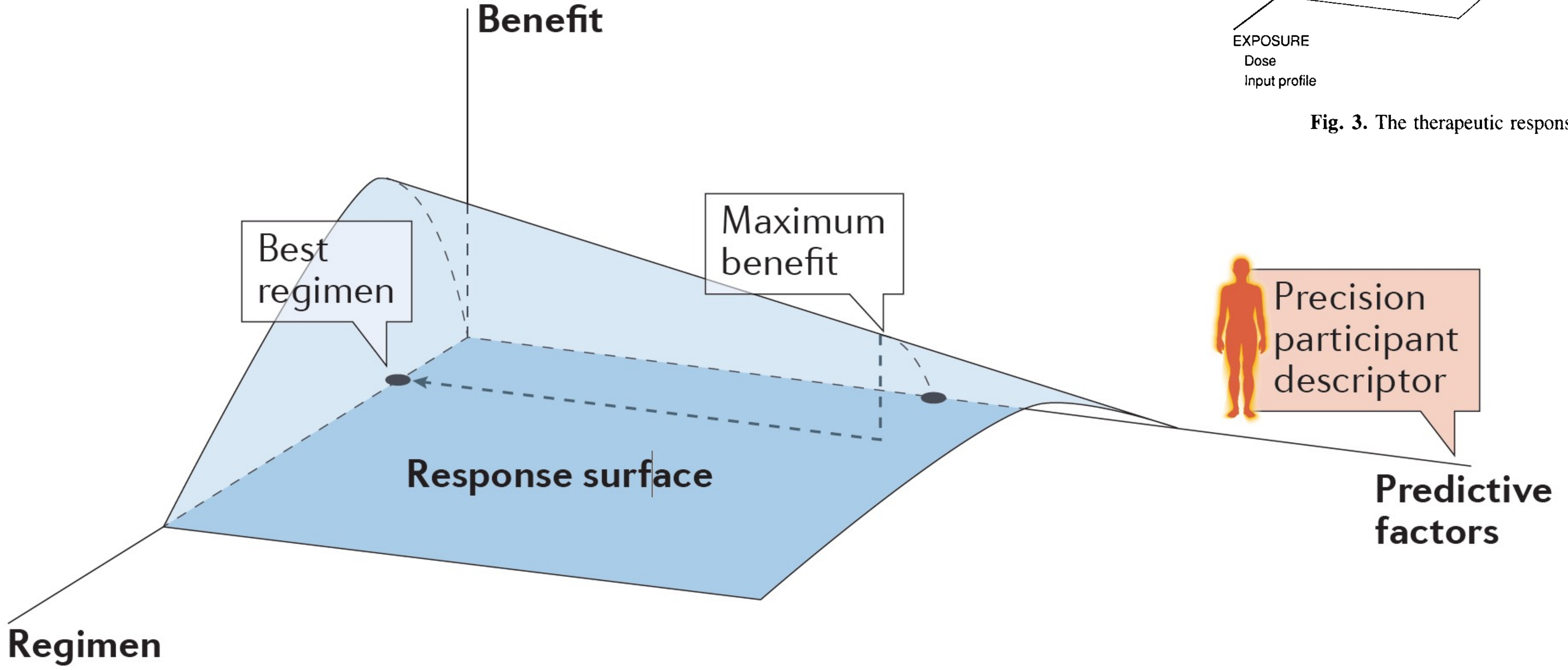


Elliott M. Antman and Joseph Loscalzo NATURE REVIEWS | **CARDIOLOGY** VOLUME 13 | OCTOBER 2016 | **591**

Why do we need higher order analyses?



Ridker et al, Eur Heart J 2016;37:1373-9



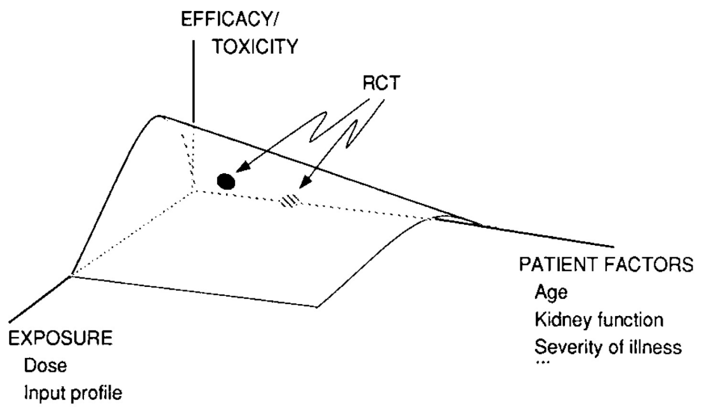


Fig. 3. The therapeutic response surface.

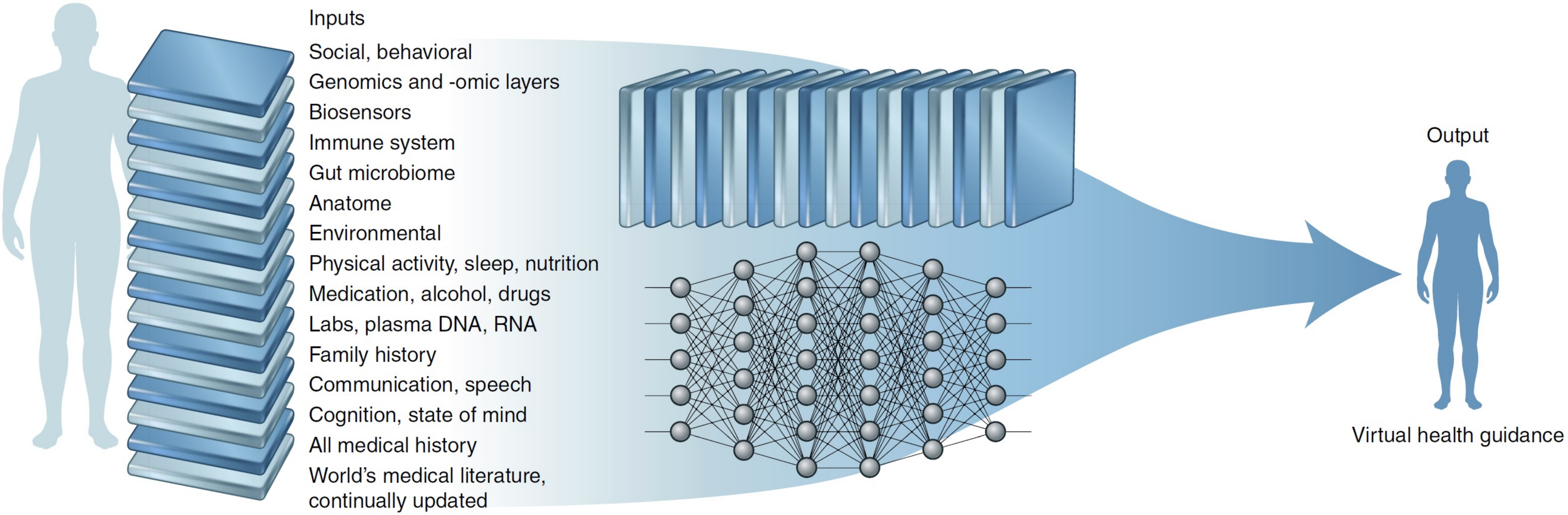


Fig. 3 | The virtual medical coach model with multi-modal data inputs and algorithms to provide individualized guidance. A virtual medical coach that uses comprehensive input from an individual that is deep learned to provide recommendations for preserving the person's health. Credit: Debbie Maizels/ Springer Nature


to generate a digital twin
Mathematical models updated with real-world data that diagnose faults and predict failure

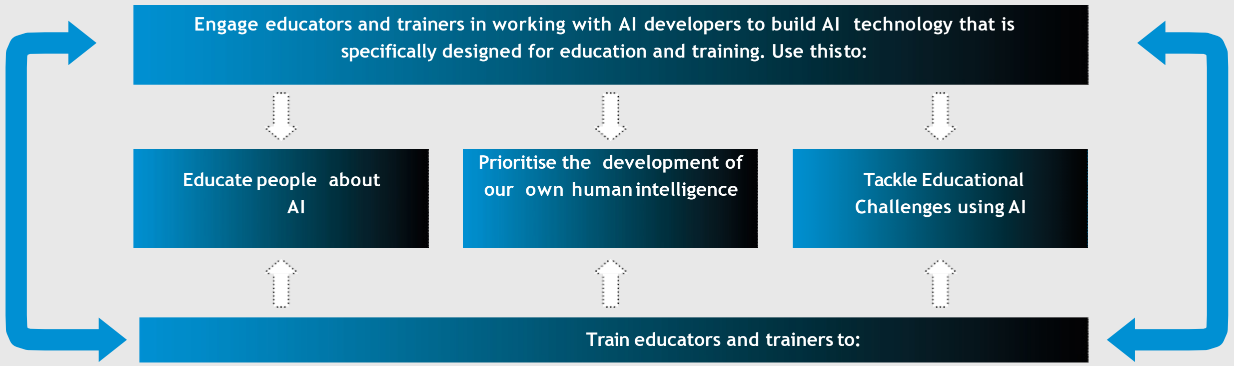


Figure 3: An intelligence approach to AI for education and training

Figure 4: HEE Digital Capabilities Framework[171]

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- What not to expect … and maybe to avoid
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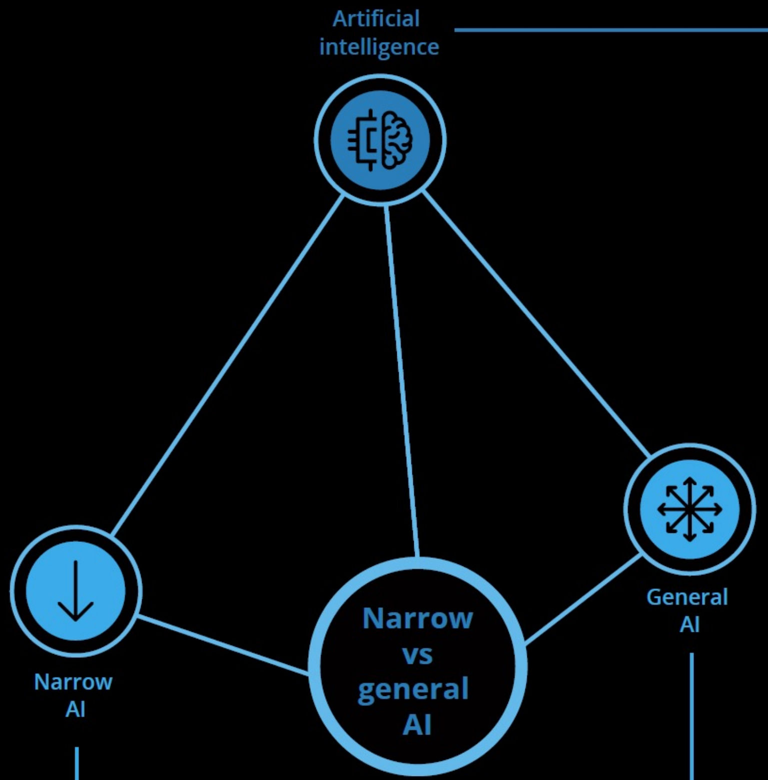
Definitions

Artificial intelligence: Deloitte defines AI as systems and applications that perform tasks that mimic or augment human intelligence, ranging from simple gaming to sophisticated decision-making agents that adapt to their environment.

People often use the term AI interchangeably with the technologies that enable it—including machine learning, deep learning, neural networks, natural language processing, rule engines, robotic process automation, and combinations of these capabilities for higher-level applications.

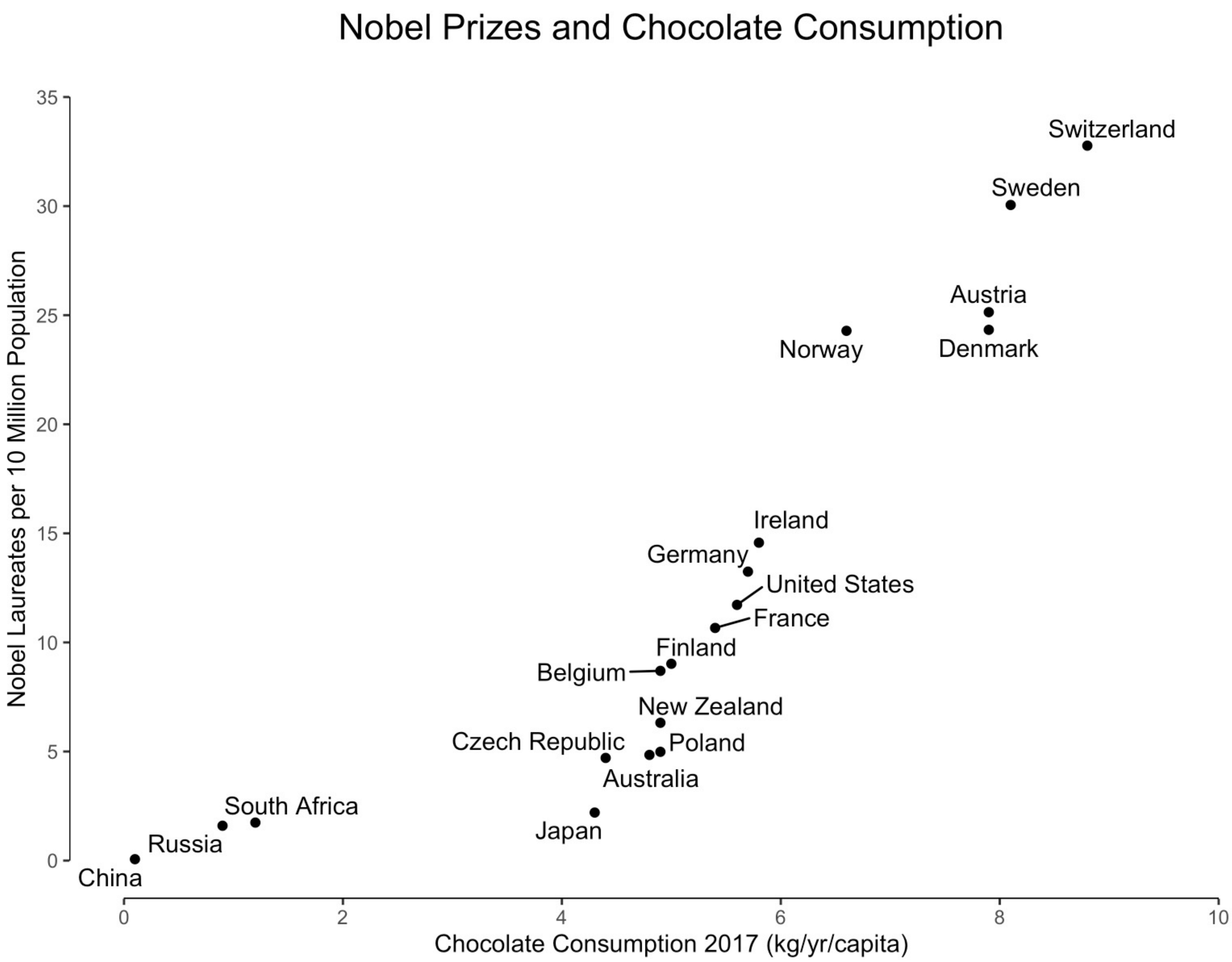


Narrow AI: Most current applications are what we call narrow AI, which means it can only perform the task it was designed to do. This means that for every problem, a specific algorithm needs to be designed to solve it.[4]

General AI: The holy grail of AI is general AI, a single system that's equal or superior to human intelligence. Today's AI applications don't exhibit this 'human-like' intelligence—an algorithm designed to drive a car, for example, wouldn't be able to detect a face in a crowd or guide a domestic robot assistant.[5]

Intuitive Psychology and Physics

Still lacking in our best AIs


Nobel Prizes and Chocolate Consumption
Nobel Laureates per 10 Million Population
Chocolate Consumption 2017 (kg/yr/capita)
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5
10
15
20
25
30
35
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2
4
6
8
10
Switzerland
Sweden
Austria
Norway
Denmark
Ireland
Germany
United States
France
Finland
Belgium
New Zealand
Czech Republic
Poland
Australia
South Africa
Russia
Japan
China

EDITORIAL

Anushka Patel, MD, PhD
Laurent Billot, MRes

Reality and Truth

Balancing the Hope and the Hype of Real-World Evidence

However, the inherent limitation of **causal inference** using observational data is increasingly lost in the discourse on real-world evidence. This is partly attributable to the misconception that real-world evidence does not require the use of randomization to avoid **confounding bias**. Methodological advancements have led to a range of "causal inference" methods, including propensity score matching or weighing, instrumental variables, and structural equations. However, even with the most robust of these methods, it is very difficult to confidently exclude the role of confounders in partially or even fully explaining observed associations, especially when the treatment effects are potentially modest albeit clinically important. In this context, the very large size of real-world data sets may not matter because **there is little advantage to increased precision if the answer has a good chance of being precisely wrong**.

Circulation. 2017;136:260–262. DOI: 10.1161/CIRCULATIONAHA.117.029233

Machine learning is **not a magic device** that can spin data into gold, though many news releases would imply that it can. Instead, it is a natural extension to traditional statistical approaches. Machine learning is a valuable and increasingly necessary tool for the modern health care system. Considering the vast amounts of information a physician may need to evaluate—such as the patient's personal history, familial diseases, genomic sequences, medications, activity on social media, admissions to other hospitals — **deriving insight to guide clinical decision** may be an overwhelming task for any one person. As more control is ceded to algorithms, it is important to note that these new algorithmic decision-making tools come with **no guarantees of fairness, equitability, or even veracity**. Although we are reluctant to repeat the cliché, even with the best machine learning algorithms the maxim of **"garbage in, garbage out"** remains true. Whether an algorithm is high or low on the machine learning spectrum, best analytic practices must be used to ensure that the end result is **robust and valid**. This is especially true in health care because these algorithms have the potential to affect the lives of millions of patients.

Curating data remains necessary, but it is a messy and laborious job

JAMA April 3, 2018 Volume 319, Number 13

Big Data

is no solution for

Bad Data

Should digital medicine be treated different?

Without a clear framework to **differentiate efficacious digital products from commercial opportunism**, companies, clinicians, and policy makers will struggle to provide the required level of evidence to realise the potential of digital medicine. The risks of digital medicine, particularly use of AI in health interventions, are concerning. Continuing to argue for **digital exceptionalism** and failing to robustly evaluate digital health interventions presents the greatest risk for patients and health systems.

www.thelancet.com **Vol 392 July 14, 2018**

Trustworthy AI
EU style

Ensure that the development, deployment and use of AI systems meets the seven key requirements for Trustworthy AI:

(1) human agency and oversight,

(2) technical robustness and safety,

(3) privacy and data governance,

(4) transparency,

(5) diversity, non-discrimination and fairness,

(6) environmental and societal well-being and

(7) accountability.

https://ec.europa.eu/futurium/en/ai-alliance-consultation/guidelines/1#Human%20

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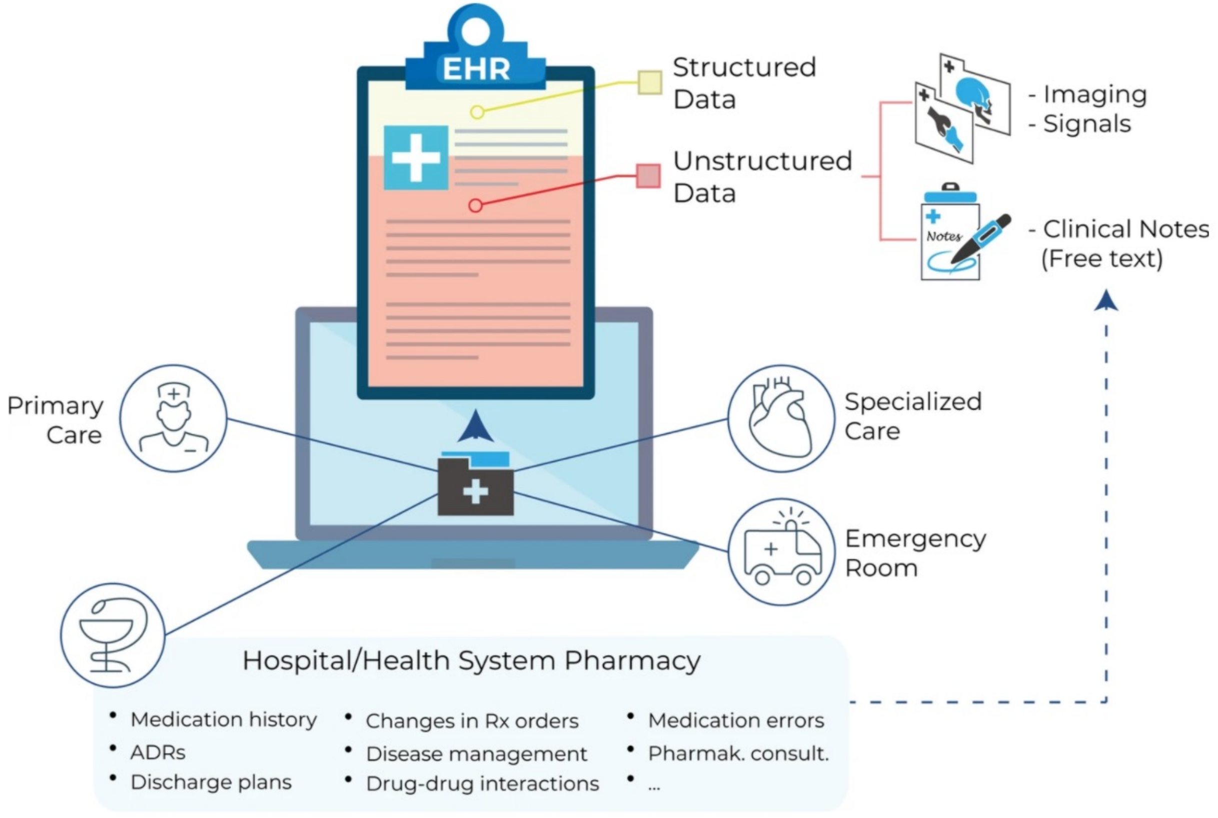
Using artificial intelligence in health-system pharmacy practice: Finding new patterns that matter

- AI tools
  - Machine Learning – Deep learning
  - AI powered robotics
  - Natural Language Processing
  - Chatbots
- Many decision-support systems with AI are in the area of drug dosing and delivery



- Identify “strange” prescriptions
  - Not rule based
  - But experience based = statistical learning
    - Less false positive and false negative alerts
    - Not only dosing errors but also predicting Adverse Drug Events

Examples

Better informed decision task

- Drug treatment decisions
- Drug selection decisions
- Drug dosing decisions

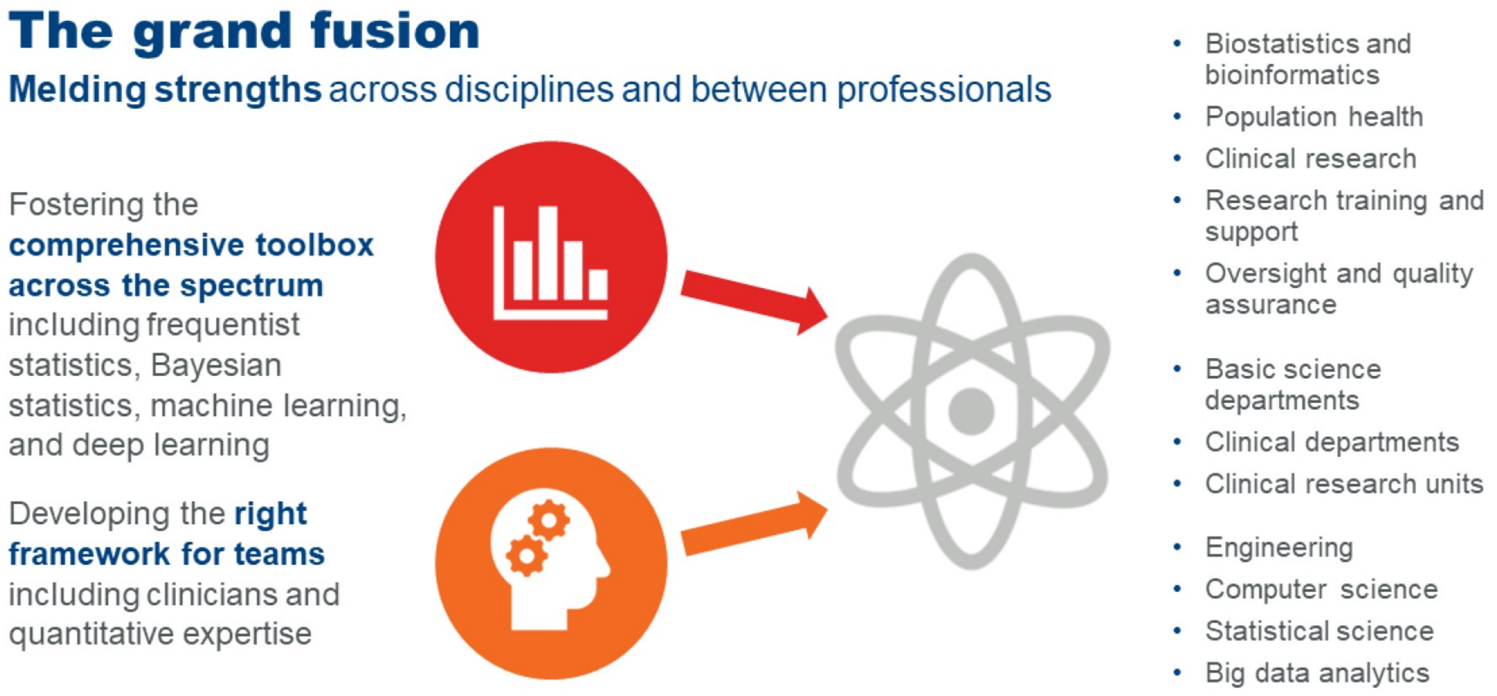
- Decisions about inventory par values
- Drug/device recall: item level visibility software in supply chain
- Image recognition for (mis)labeled products
- …

Questions to ask

1. How would this model provide value in our organization?
2. What would people do with the model's outputs or predictions?
3. How accurate is the model (consider discrimination and calibration)?
4. Is that accuracy clinically significant and useful?
5. Does the population used to train the model reflect the population served by our organization?
6. How thoroughly was the model validated? What did prospective external validation show?
7. How well does the model maintain accuracy with changing inputs (drift)?
8. How can we collect the data necessary to use this model in production?
9. Do we need near real-time data feeds to use the model in production, and can we get them?
10. Is the model technically feasible in our setting? Who would implement and maintain the technical infrastructure?
11. What could be the potential unintended consequences of using the model at our organization?

The Future is in Sharing, Cooperation and Transparancy

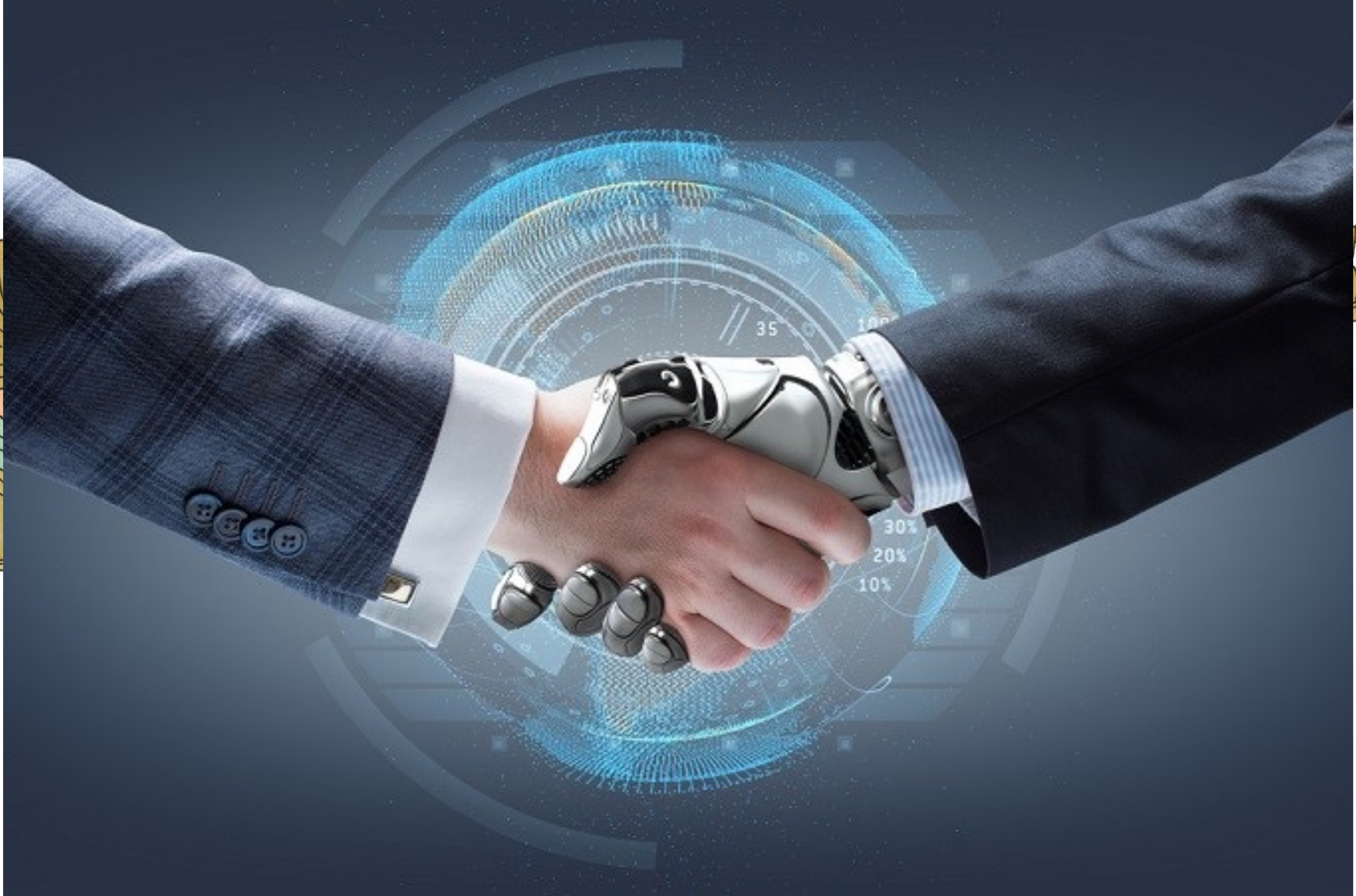
- Between patients and care providers
- Between systems: Interoperability
- Between research groups
- Between disciplines
  - Knowledge driven
  - Data supported



to manage the health care system's ever-increasing **complexity,** and
to curb ever-escalating **costs**

Take Home Messages Augmented Intelligence

- To overcome the complexity and the vast increase in relevant information for making decisions about diagnosis and treatment, we need the help of data crunching software and augmented intelligence using real world information
  - This real-world evidence is complementary to hypothesis driven, RCT-type research evidence
  - To optimally implement this strategy a system approach is required: the self-learning health system
- Machine learning should not be a black box but provide “explainability”
- Needs scientific evaluation
  - As for other practices in medicine
  - Nothing is good or bad in itself; it is how it is used or applied
- Get used to deal with probabilities rather than certainties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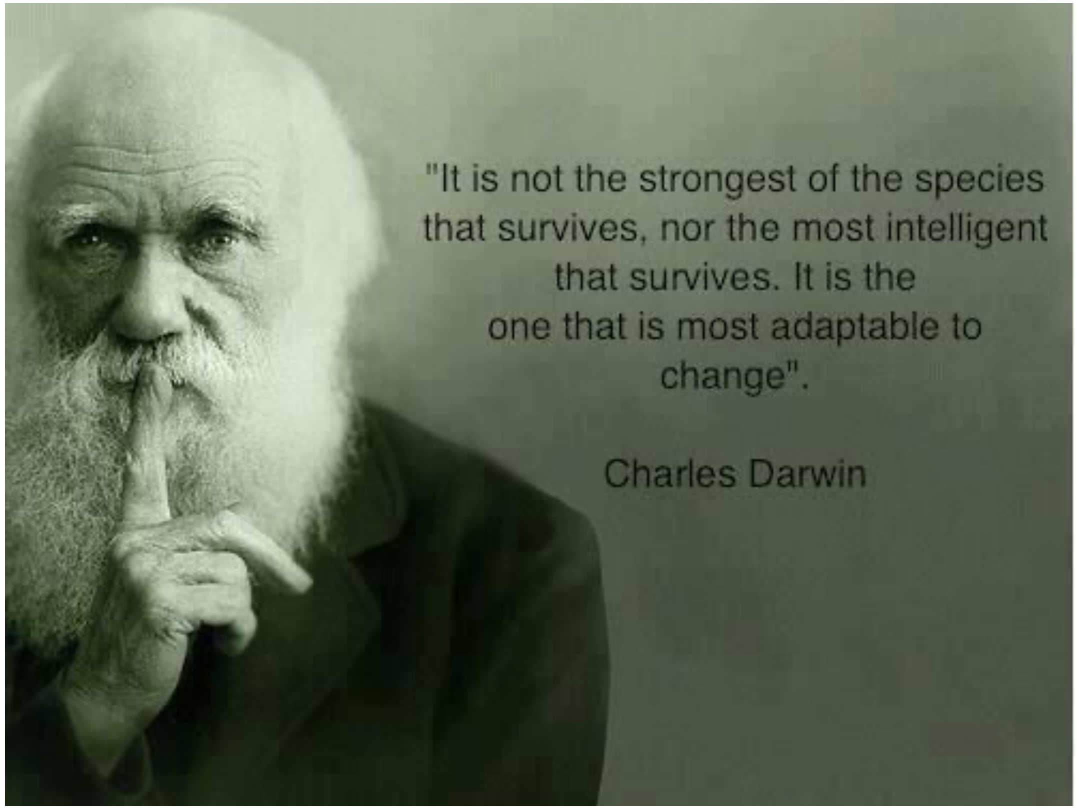
"It is not the strongest of the species that survives, nor the most intelligent that survives. It is the one that is most adaptable to change".
Charles Darwin


RUBES
Technology advances; people stay the same.

Further reading