

# Artificial Intelligence for Digital Health – Course Overview

Artificial Intelligence for Digital Health (AID)

M.Sc. in Digital Health – University of Pisa

Davide Bacciu ([davide.bacciu@unipi.it](mailto:davide.bacciu@unipi.it))

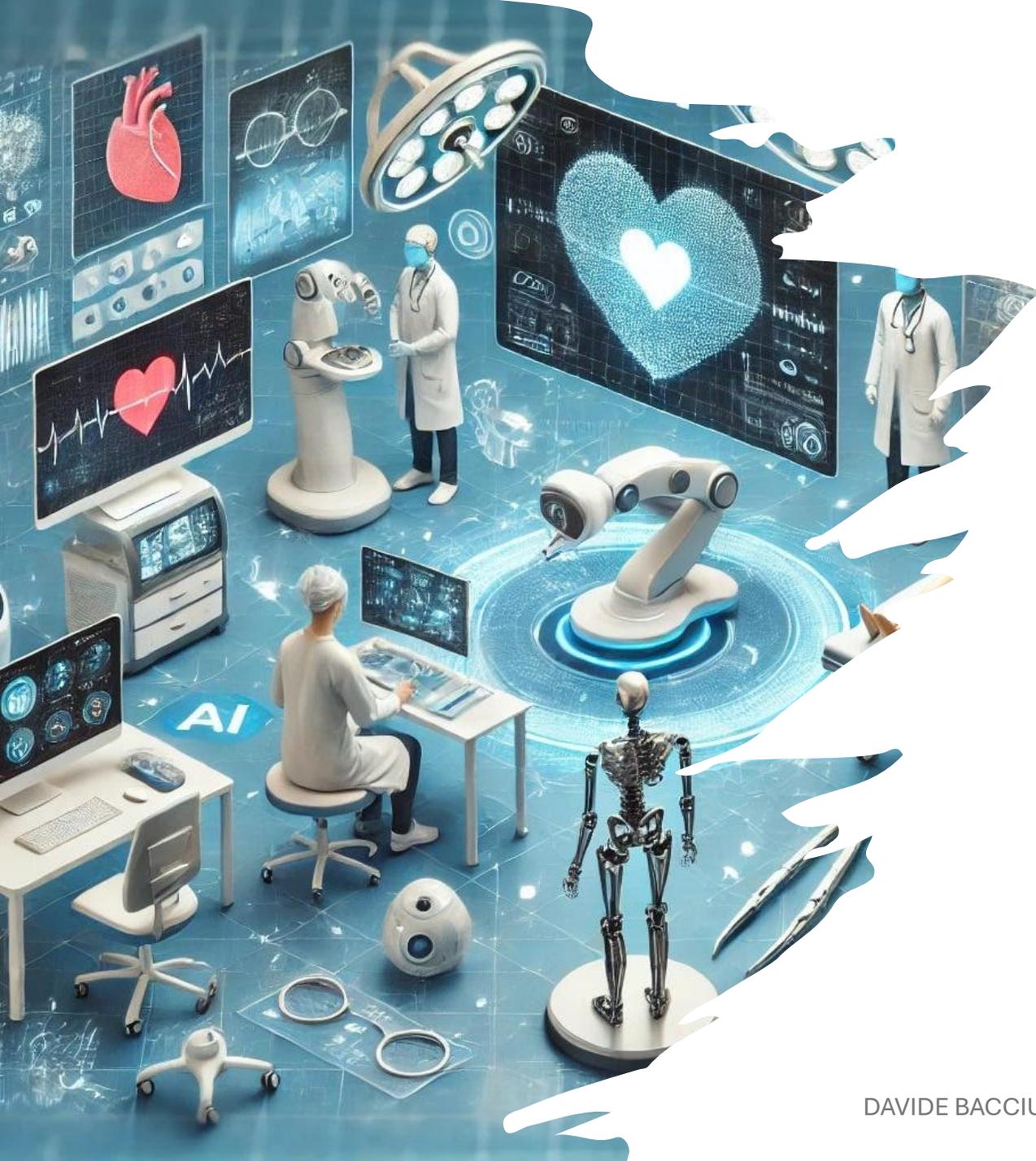
Marco Podda ([marco.podda@unipi.it](mailto:marco.podda@unipi.it))



# Lecture Outline

- Course overview
- A history of Artificial Intelligence in healthcare and life sciences
- Perks of biomedical/health data
- Course execution and examination

# Course Overview



# Course objectives

Train ICT specialists who

- Understand the **challenges of working with health data**, including physiological time-series, clinical text, and medical imaging
- Know the **leading AI-based methodologies** and understand how to apply them to relevant digital health problems
- Have **practical insights into the main AI technological solutions and programming resources** and how to use them in digital health
- Understand how to **robustly use AI methodologies and develop trusted AI-based digital health applications**

# Prerequisites

Foundational knowledge of

- Calculus and linear algebra ([Appendix B, Prince textbook](#))
- Elements of probability and statistics ([Appendix C, Prince textbook](#))
- Basics of optimization ([compendium](#))

Programming experience with [Python](#) is assumed for practical labs

- Previous experience with AI/ML Python libraries is a plus

# Organization of Course Contents

- **Preliminaries**
  - Course overview
  - Probability and statistics refresher for AI
- **Fundamentals of AI in healthcare**
  - Machine learning basics and baselines (regression, neural networks)
  - Risk stratification and survival analysis
  - Probabilistic/Bayesian models and causality
- **Deep Learning**
  - Deep learning basics and baselines
  - AI for medical imaging (classification, segmentation, recognition)
  - AI for sequential data in healthcare
  - AI for clinical text and language models for health
- **Advanced topics**
  - Graphs in Health and Life Sciences
  - AI applications in healthcare
  - Research directions and challenges in AI for health
  - Guest lectures

Hands-on  
laboratories will  
complement  
methodological  
lectures

# Course Instructors



**Davide Bacciu (Lecturer)** - [davide.bacciu@unipi.it](mailto:davide.bacciu@unipi.it)

- Professor of Machine Learning - Head of Pervasive AI lab
- Lecturer of deep and generative learning at the M.Sc. in AI
- Startup: quantitative brain techs, AI for harsh environments, AI for regulatory compliance
- Office hours: on request, via mail



**Marco Podda (Laboratory Lecturer)** - [marco.podda@unipi.it](mailto:marco.podda@unipi.it)

- Researcher, Computer Science Department
- Learning from graph data and generative models
- Applications in healthcare domain
- Office hours: on request, via mail

# Dates, times and format

Day	Time
Tuesday – Room M1	14.15-16.00
Wednesday – Room H	14.15-16.00
Thursday – Room C1	14.15-16.00

- Course comprises ~24 lectures and ~12 labs
- Course lectures and labs will be given in-person (**no streaming**)
- Video recording of the lectures will be made available on the shared Teams drive (**best effort, no guarantees**)

# Resources

Reference Webpage on Moodle:

<https://elearning.di.unipi.it/course/view.php?id=1024>

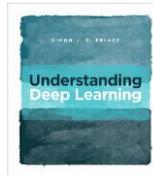
Here you will find

- Course information and up-to-date news
- Lecture slides
- Articles and course materials
- Project assignments and exams materials



Make sure to **subscribe** to the course on Moodle

# Reference Books



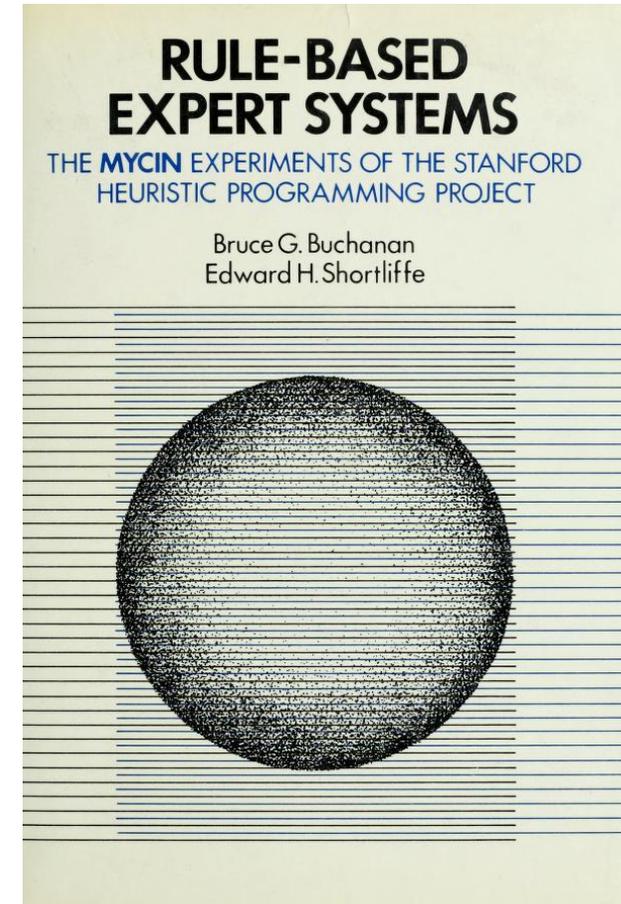
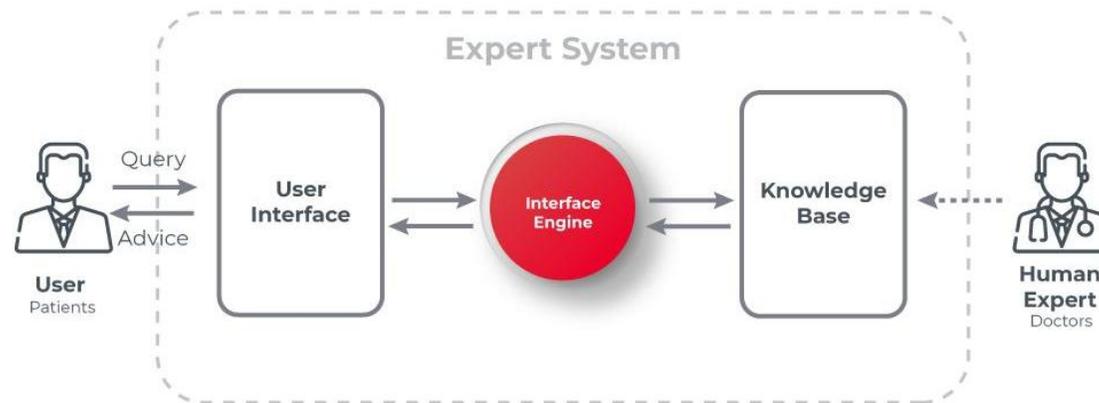
- Reference for foundational AI/ML knowledge
  - Simon J.D. Prince, [Understanding Deep Learning](#), MIT Press (2023)
  - Additional materials on the [book website](#)
- Reference for AI in healthcare
  - G.J. Simon, C. Aliferis, [AI and ML in health Care and Medical Sciences](#), Springer, 2024
- Both available open-source

# AI in health and life sciences

# AI in healthcare: a long-standing quest

The **expert systems** era (1970-1980)

- **MYCIN**: identify bacteria causing severe infections and propose a therapy
- Rule-based (600) + simple inference engine

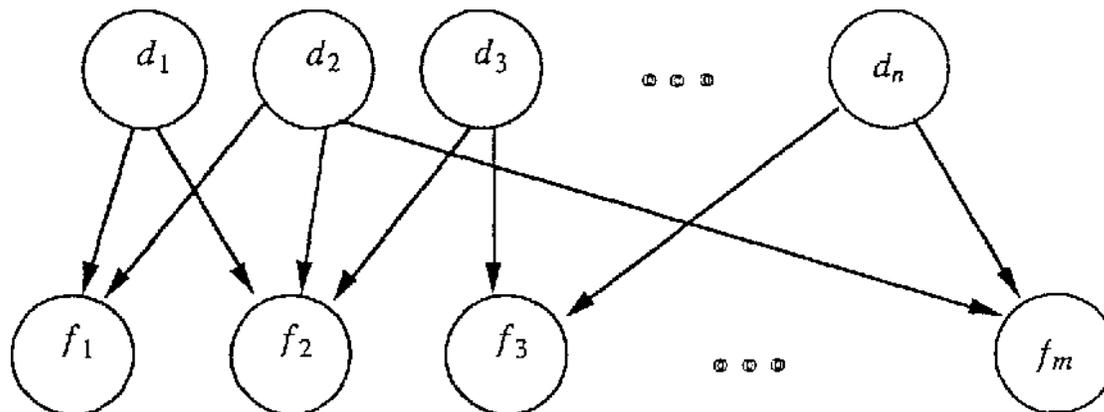


# 1980s: The rise of Bayesian methods

15 person-years  
of work

## INTERNIST-1/Quick Medical Reference

- Introduced decision trees and belief networks
- The fundamentals of Bayesian networks and approximated inference



### Medical Informatics

#### The INTERNIST-1/QUICK MEDICAL REFERENCE Project—Status Report

RANDOLPH A. MILLER, MD; MELISSA A. McNEIL, MD; SUE M. CHALLINOR, MD; FRED E. MASARIE, Jr, MD, and JACK D. MYERS, MD, Pittsburgh

*INTERNIST-1 and its successor, QUICK MEDICAL REFERENCE (QMR), are computer programs designed to provide health care professionals with diagnostic assistance in general internal medicine. Both programs rely on the INTERNIST-1 computerized knowledge base, which comprehensively describes 570 diseases in internal medicine. The philosophies behind the development of each program differ. Whereas INTERNIST-1 functions solely as a high-powered diagnostic consultant program, the QMR program acts more as an information tool, providing users with multiple ways of reviewing and manipulating the diagnostic information in the program's knowledge base. At the lowest level, the program can be viewed as an electronic textbook of medicine. In addition, the QMR program has the ability to assist users with generating hypotheses in complex patient cases. The QMR program has not been evaluated formally as an information tool for practicing physicians. A preliminary study indicates that QMR's case-analysis capabilities are of potential benefit in most patients in internal medicine admitted for diagnostic evaluation.*

(Miller RA, McNeil MA, Challinor SM, et al: The INTERNIST-1/QUICK MEDICAL REFERENCE project—Status report, *In Medical informatics [Special Issue]. West J Med* 1986 Dec; 145:816-822)

**I**NTERNIST-1 and its successor, QUICK MEDICAL REFERENCE (QMR), are computer programs designed to provide health care professionals with diagnostic assistance in general internal medicine. We review the past accomplishments, current status and future objectives of our research at the University of Pittsburgh related to the INTERNIST-1/QMR project. Project objectives continue to be to extend and improve the comprehensive INTERNIST-1 medical knowledge base for diagnosis in general internal medicine and to further develop and evaluate related diagnostic information-processing programs.

#### The INTERNIST-1 Project

INTERNIST-1, an experimental computer-based diagnostic consultant system for general internal medicine, was developed and evaluated by Myers, Pople and Miller and co-workers.<sup>1-7</sup> The original goal of the project, as conceived in 1972-1973, was to develop a diagnostic computer program that could functionally mimic the reasoning of an expert clinician. Given patient data in the form of historical facts, current

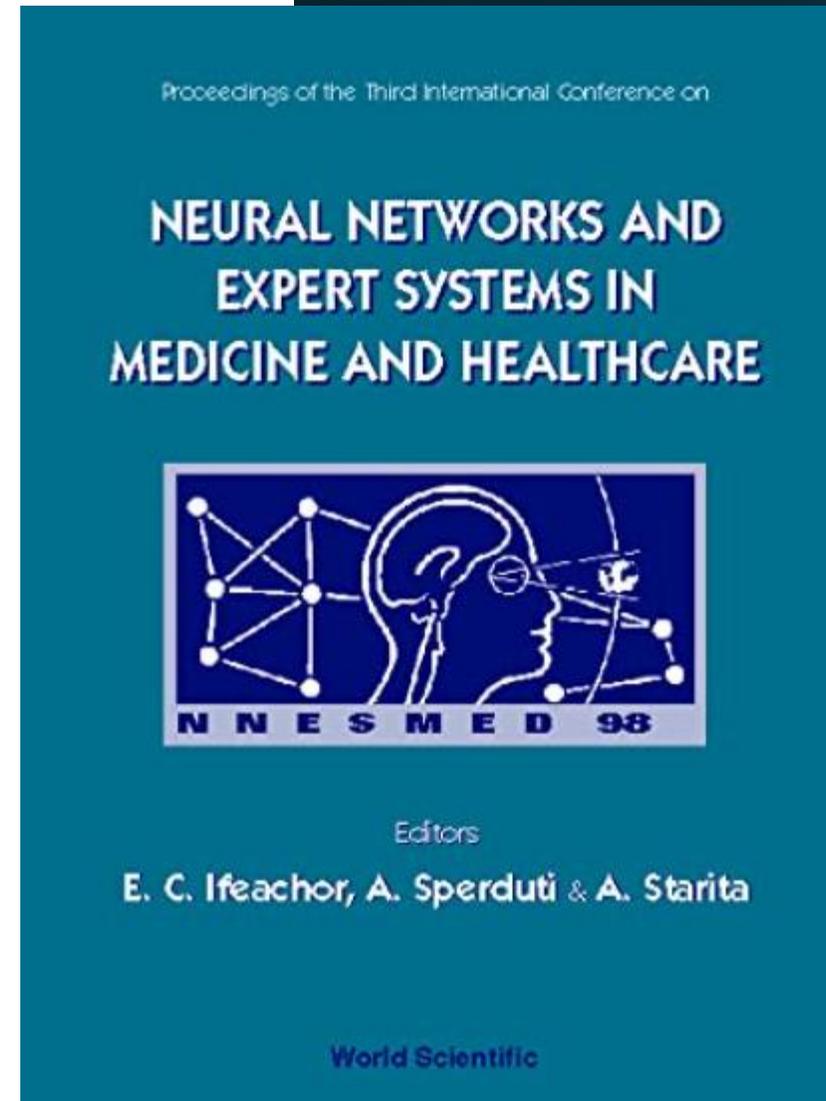
symptoms, findings from a physical examination and laboratory results, the INTERNIST-1 program was designed to formulate differential diagnoses and then resolve them by asking questions. The program could make multiple and complex diagnoses in challenging patient cases.

In 1981 a retrospective evaluation of the INTERNIST-1 program was conducted using clinicopathological conference (CPC) cases published in *The New England Journal of Medicine* (NEJM).<sup>3</sup> The study was done via retrospective case analyses so as not to subject patients to the risk of possible diagnostic errors by the computer program. The NEJM CPC cases were chosen because they contained enough detail to permit computer analysis. The diagnostic performance of the INTERNIST-1 program (for cases where the ultimate anatomic diagnoses were within the program's knowledge base) was found to be qualitatively similar to that of the clinicians caring for patients at an academic teaching hospital. The program's ability to arrive at the "correct" diagnosis, however, was not as good as that of the invited clinical expert case discussants. The study identified several deficiencies in the

From the Division of General Internal Medicine, Department of Medicine, University of Pittsburgh School of Medicine, Pittsburgh. The QUICK MEDICAL REFERENCE project has been supported by grants from the CAMDAT Foundation of Farmington, Connecticut, and from the Department of Medicine of the University of Pittsburgh School of Medicine. Dr Miller is recipient of Research Career Development Award K04-00084 from the National Library of Medicine. Reprint requests to Randolph A. Miller, MD, 165A Lothrop Hall, 190 Lothrop St, University of Pittsburgh School of Medicine, Pittsburgh, PA 15261.

# 1990s: Neural networks enter medicine

- Nearly 100 studies on neural networks on clinical data in 1990
- Networks with few selected and hand engineered inputs
- Issues:
  - Did not fit well into clinical workflow
  - Hard to source enough training data
  - Poor generalization

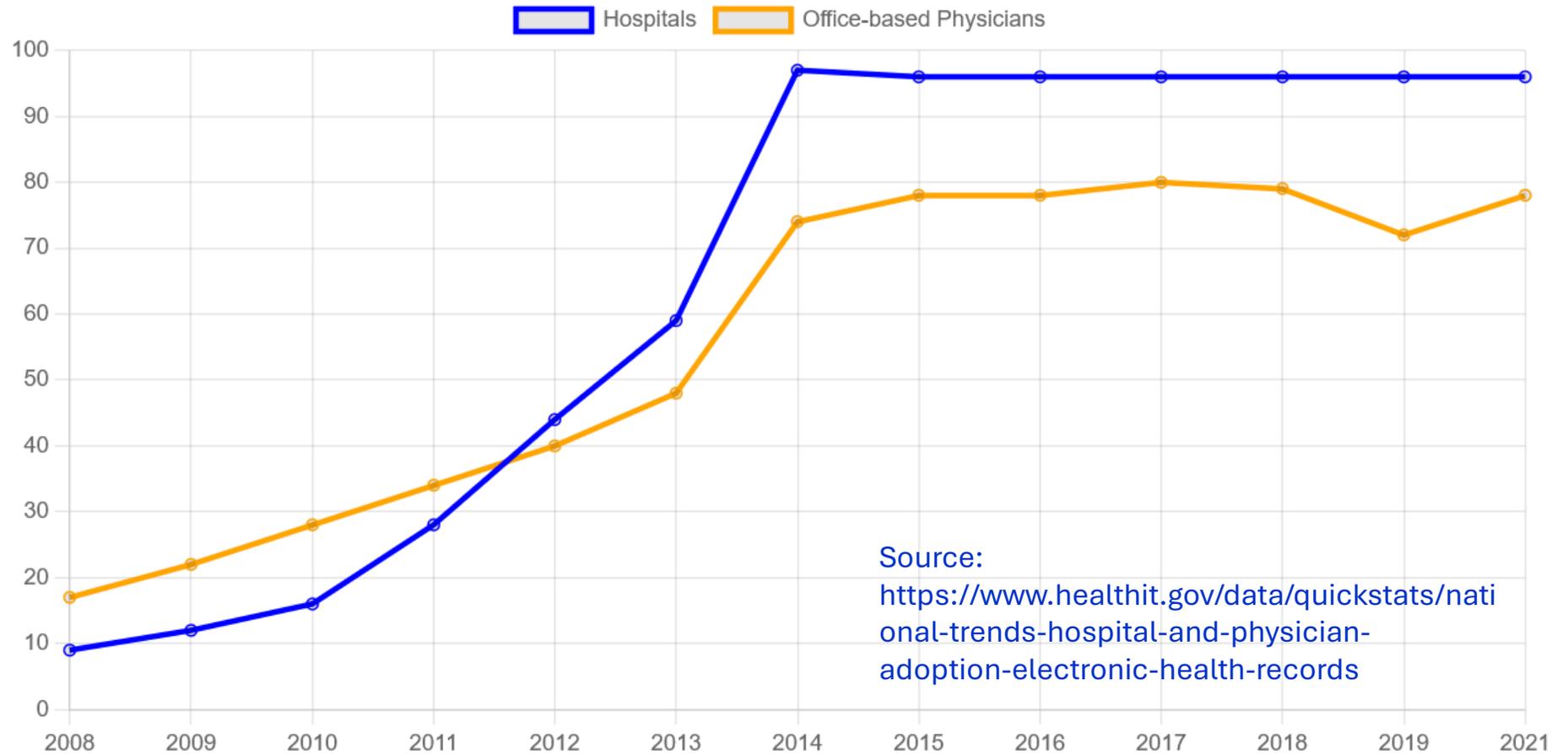


**Table 1** • 25 Neural Network Studies in Medical Decision Making\*

Subject	No. of Examples		P†	Network	D‡	Accuracy§	
	Training	Test				Neural	Other
Breast cancer <sup>4</sup>	57	20	60	9-15-2	0.6	80	75
Vasculitis <sup>2</sup>	404	403	73	8-5-1	8.0	94	—
Myocardial infarction <sup>6</sup>	351	331	89	20-10-10-1	1.1	97	<del>84</del>
Myocardial infarction <sup>8</sup>	356	350	87	20-10-10-1	1.1	97	<del>84</del>
Low back pain <sup>11</sup>	100	100	25	50-48-2	0.2	90	90
Cancer outcome <sup>13</sup>	5,169	3,102	—	54-40-1	1.4	0.779	0.776
Psychiatric length of stay <sup>17</sup>	957	106	73	48-400-4	0.2	74	76
Intensive care outcome <sup>23</sup>	284	138	91	27-18-1	0.5	0.82	0.82
Skin tumor <sup>21</sup>	150	100	80	18	—	80	90
Evoked potentials <sup>35</sup>	100	67	52	14-4-3	3.8	77	77
Head injury <sup>47</sup>	500	500	50	6-3-3	20	66	77
Psychiatric outcome <sup>54</sup>	289	92	60	41-10-1	0.7	79	—
Tumor classification <sup>55</sup>	53	6	38	8-9-3	1.4	99	88
Dementia <sup>57</sup>	75	18	19	80-10-7-7	0.6	61	—
Pulmonary embolism <sup>59</sup>	607	606	69	50-4-1	2.9	0.82	0.83
Heart disease <sup>62</sup>	460	230	54	35-16-8-2	3	83	84
Thyroid function <sup>62</sup>	3,600	1,800	93	21-16-8-3	22	98	93
Breast cancer <sup>62</sup>	350	175	66	9-4-4-2	10	97	96
Diabetes <sup>62</sup>	384	192	65	8-4-4-2	12	77	75
Myocardial infarction <sup>63</sup>	2,856	1,429	56	291-1	9.8	85	—
Hepatitis <sup>65</sup>	39	42	38	4-4-3	3.3	74	79
Psychiatric admission <sup>76</sup>	319	339	85	53-1-1	6.0	91	—
Cardiac length of stay <sup>83</sup>	713	696	73	15-12-1	3.5	0.70	—
Anti-cancer agents <sup>89</sup>	127	141	25	60-7-6	1.5	91	86
Ovarian cancer <sup>91</sup>	75	98	—	6-6-2	2.6	84	81
MEDIAN VALUE	350	175	71	20	2.8		

# Then things started taking a favourable path

Adoption of Electronic Health Records (EHRs) began a steady growth



Source:

<https://www.healthit.gov/data/quickstats/national-trends-hospital-and-physician-adoption-electronic-health-records>

# Availability of biobanks and resources



The new PhysioNet website is available at <https://physionet.org>.

PhysioBank is a large and growing archive of physiological data. Please see the [About PhysioBank](#) page for more information about its data, and useful tools for finding, downloading, and visualizing it.

This page lists all currently available databases in the PhysioBank archives:

- [Clinical Databases](#) - Data from critical care clinical settings that may include demographics, vital sign measurements made at the bedside, laboratory test results, procedures, medications, caregiver notes, images and imaging reports, and mortality (both in and out of hospital).
- [Waveform Databases](#) - High resolution continuous recordings of physiological signals. Waveform databases are organized according to their signal and annotation types:
  - [Multi-Parameter Databases](#). Available signals vary, but may include ECG, continuous invasive blood pressure, respiration, oxygen saturation, and EEG, among others.
  - [ECG Databases](#). Also see [Multi-Parameter Databases](#), most of which include ECG signals.
  - [Interbeat \(RR\) Interval Databases](#). These contain beat annotations obtained from ECG recordings, but the ECG

On this page:

- [Clinical Databases](#)
- [Waveform Databases](#)
  - [Multi-Parameter Databases](#)
  - [ECG Databases](#)
  - [Interbeat \(RR\) Interval Databases](#)
  - [Other Cardiovascular Databases](#)
- [Gait and Balance Databases](#)
- [Neuroelectric and Myoelectric Databases](#)
- [Image Databases](#)
- [Synthetic Databases](#)
- [Other Databases](#)
- [Computing in Cariology Challenge Databases](#)
- [Other Databases](#)

# Standardization

**ICD-10 Version:2019**

Search  [Advanced Search] ICD-10 Versions - Languages Info

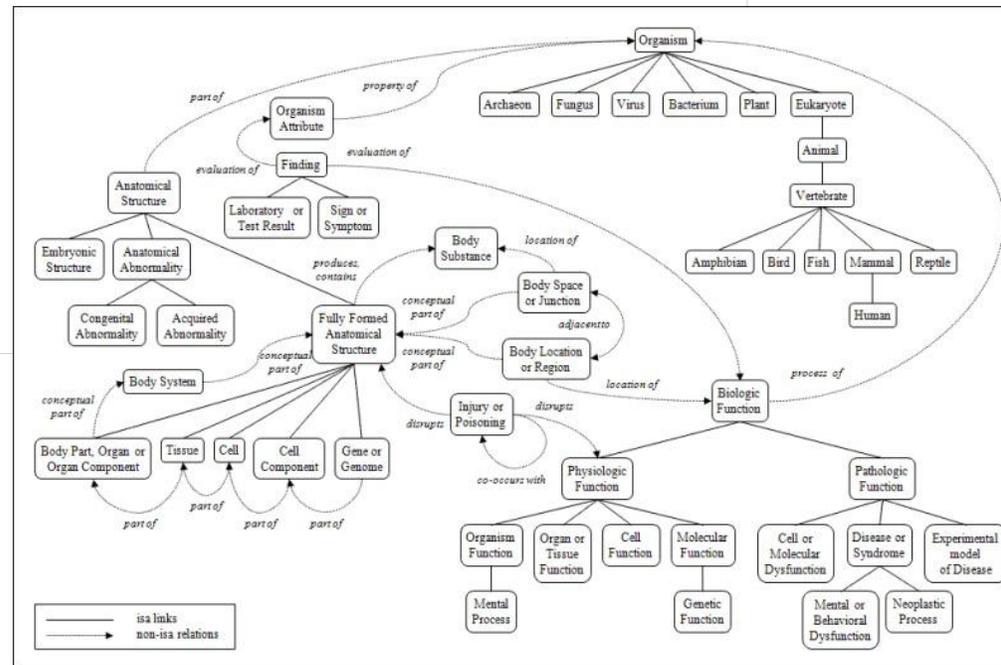
**ICD-10 Version:2019**

- I Certain infectious and parasitic diseases
- II Neoplasms
- III Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism
- IV Endocrine, nutritional and metabolic diseases
- V Mental and behavioural disorders
- VI Diseases of the nervous system
- VII Diseases of the eye and adnexa
- VIII Diseases of the ear and mastoid process
- IX Diseases of the circulatory system
- X Diseases of the respiratory system
- XI Diseases of the digestive system
- XII Diseases of the skin and subcutaneous tissue
- XIII Diseases of the musculoskeletal system and connective tissue
- XIV Diseases of the genitourinary system
- XV Pregnancy, childbirth and the puerperium
- XVI Certain conditions originating in the perinatal period
- XVII Congenital malformations, deformations and chromosomal abnormalities
- XVIII Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified
- XIX Injury, poisoning and certain other consequences of external causes
- XX External causes of morbidity and mortality

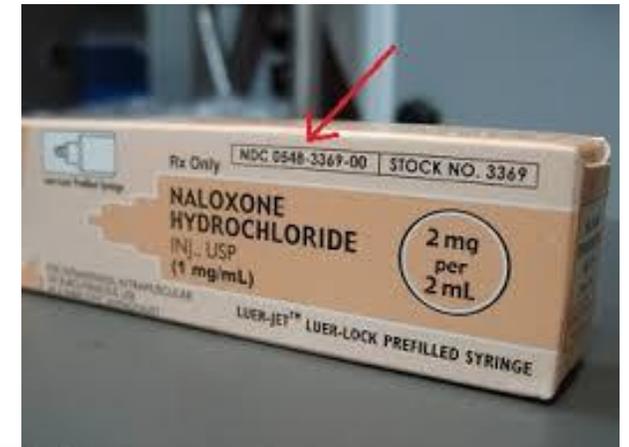
**International Statistical Classification of Diseases and Related Health Problems 10th Revision**

You may browse the classification by using the hierarchy on the left or by using the search functionality

More information on how to use the online browser is available in the Help



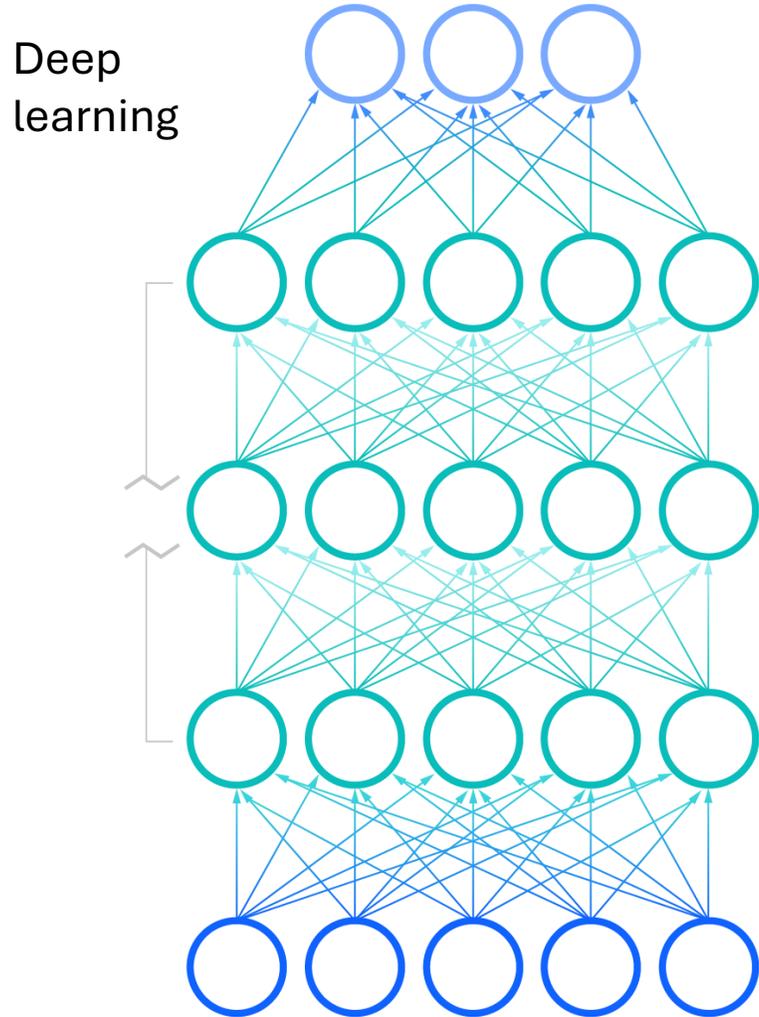
## ICD: Classification of Diseases



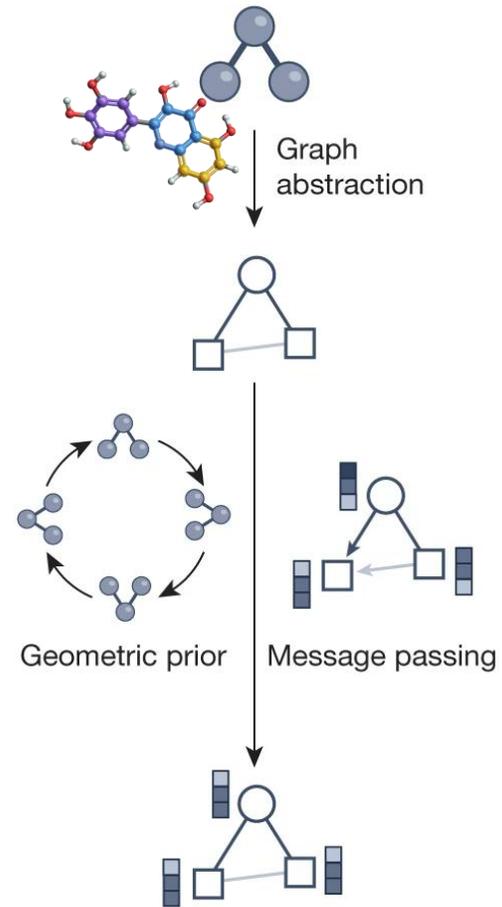
National drug codes

Unified Medical Language System: millions of medical concepts

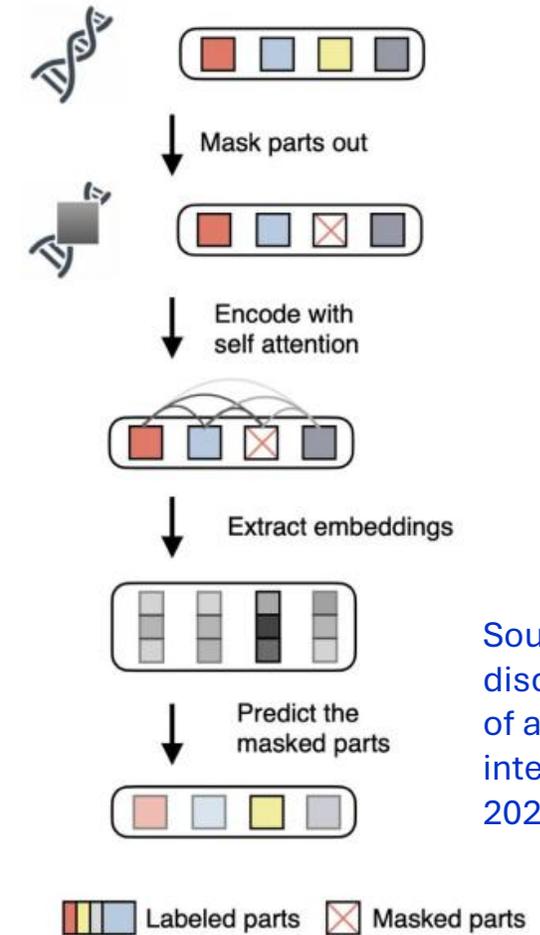
# Key AI advances



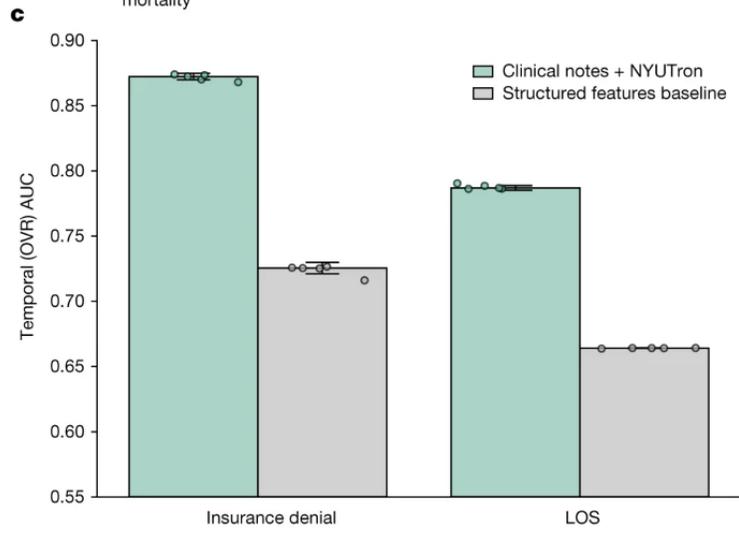
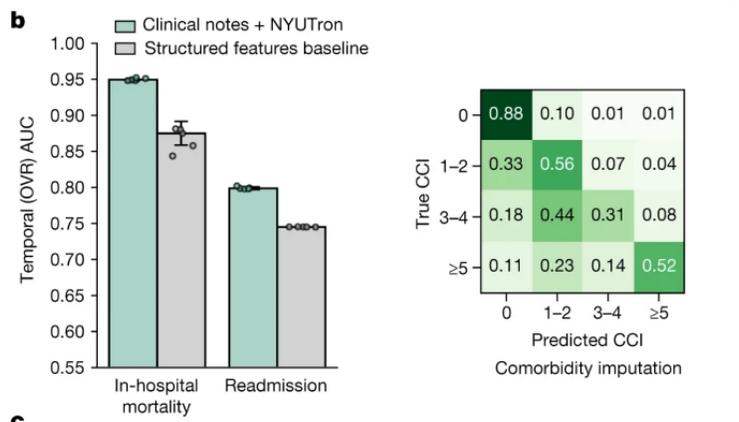
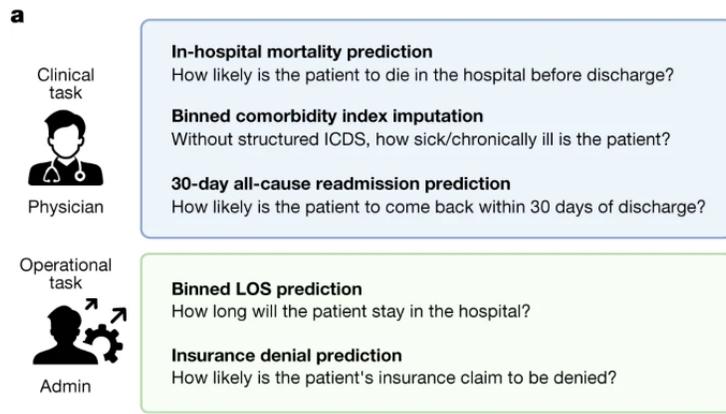
## Learning from complex data



## Self-supervised learning

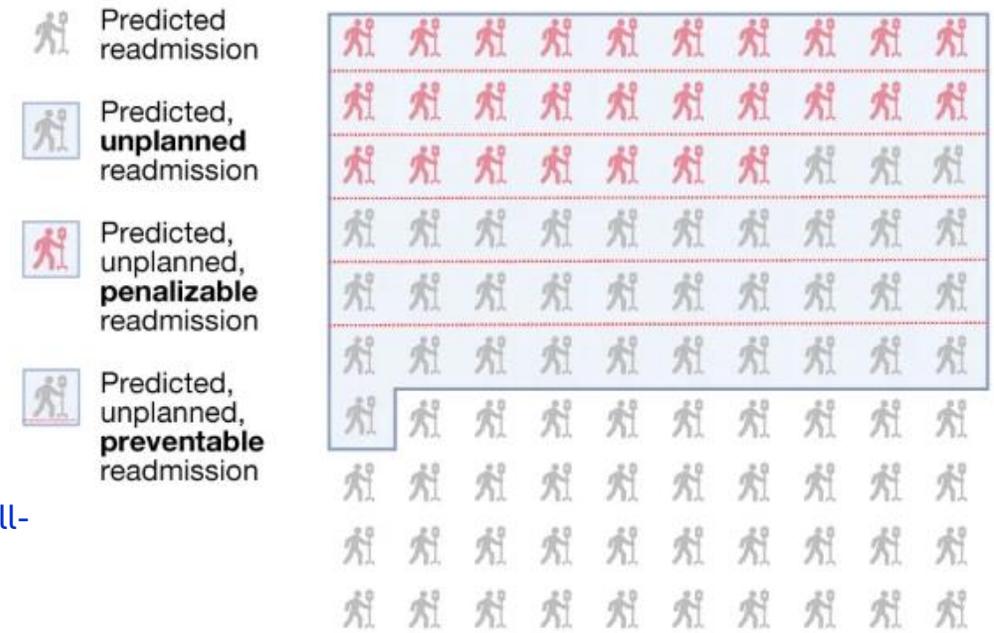


Source: Scientific discovery in the age of artificial intelligence, Nature 2023



# AI in Digital Health in the LLM era

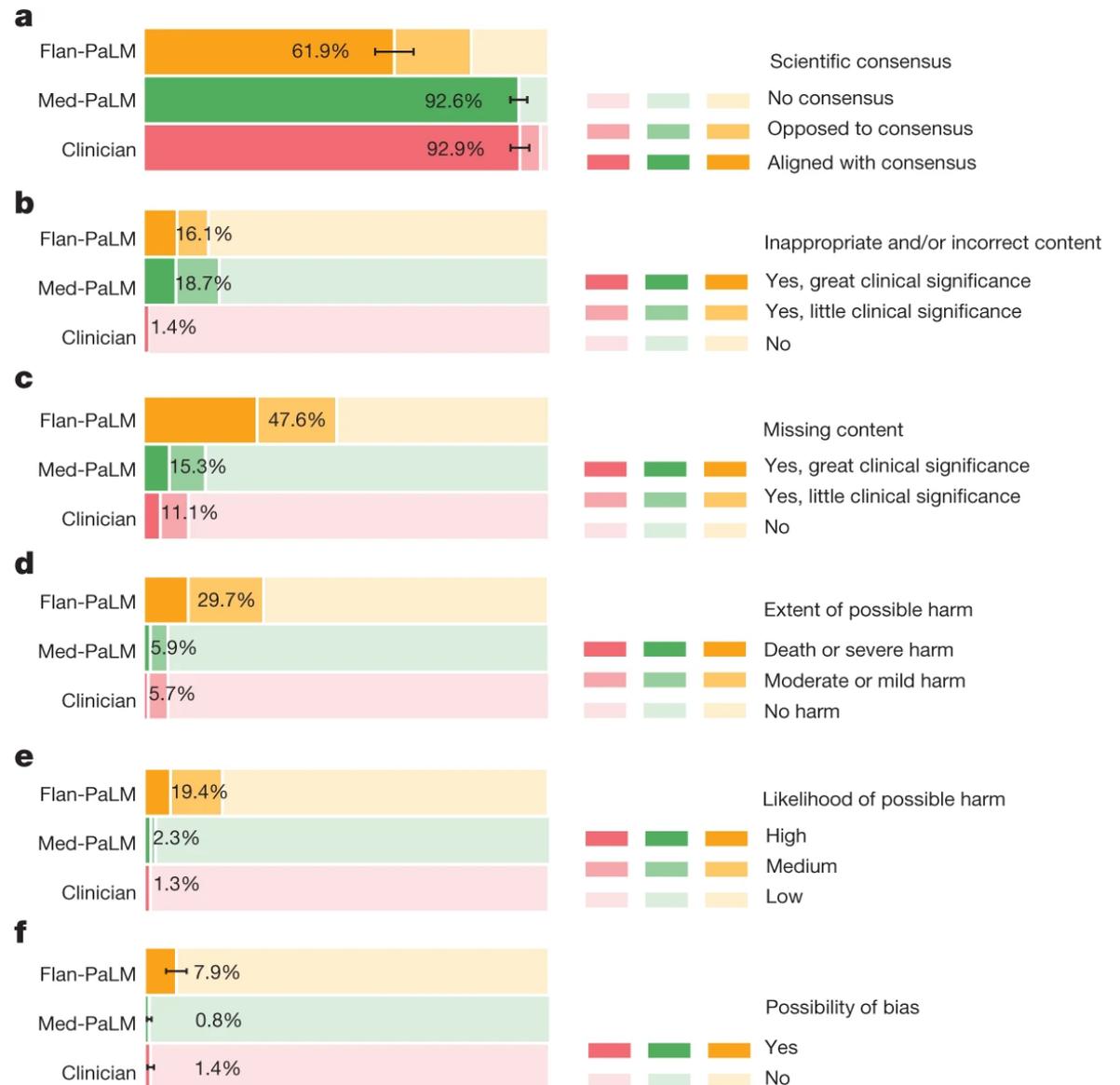
Assessment of an LLM-based agent (**NYUTron**) for multiple clinical and operational healthcare tasks



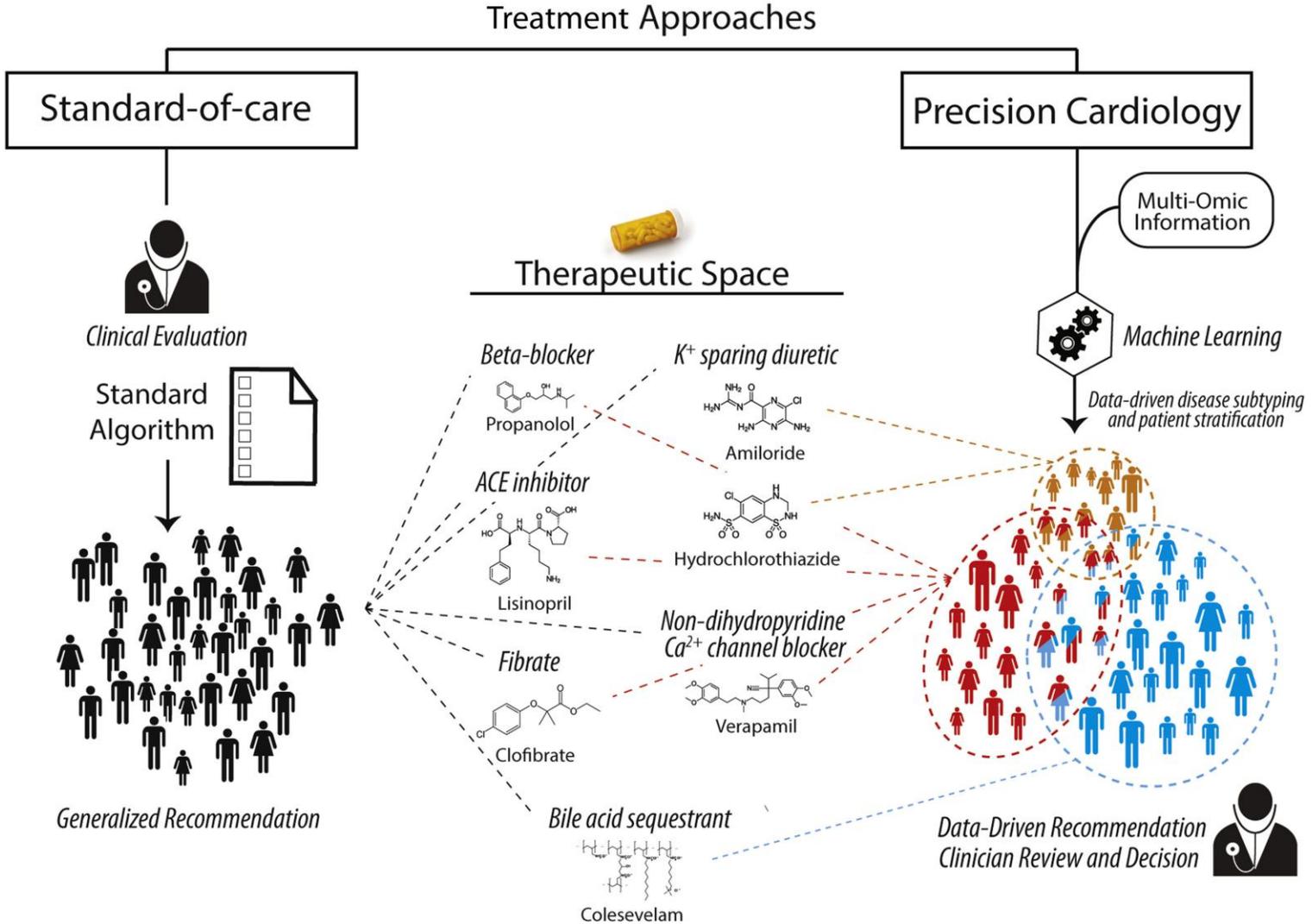
Health system-scale language models are all-purpose prediction engines, Nature 2023

# Assessing AI on clinical knowledge

Large language models encode clinical knowledge, Nature 2023

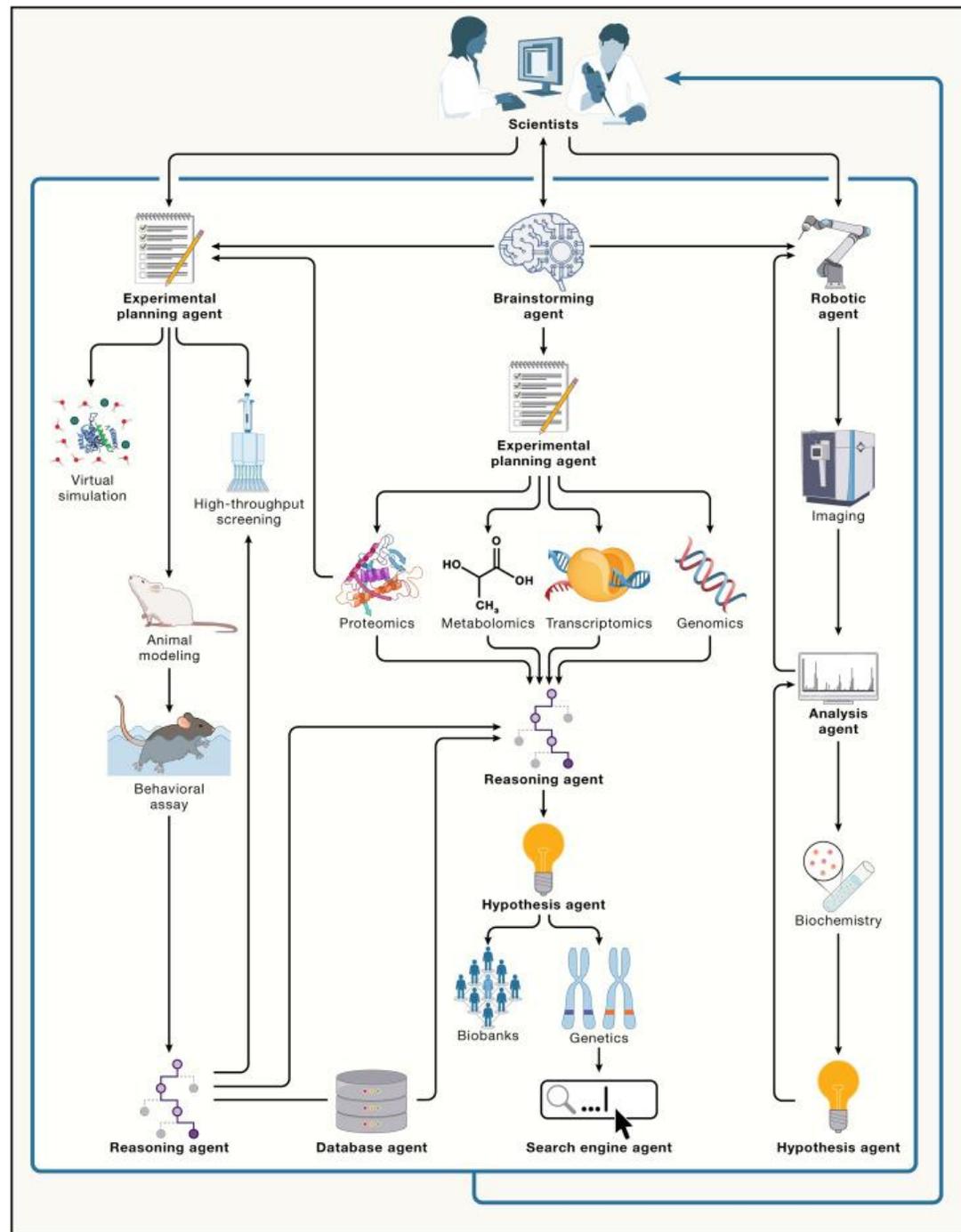


# General Vs Personalized Medicine

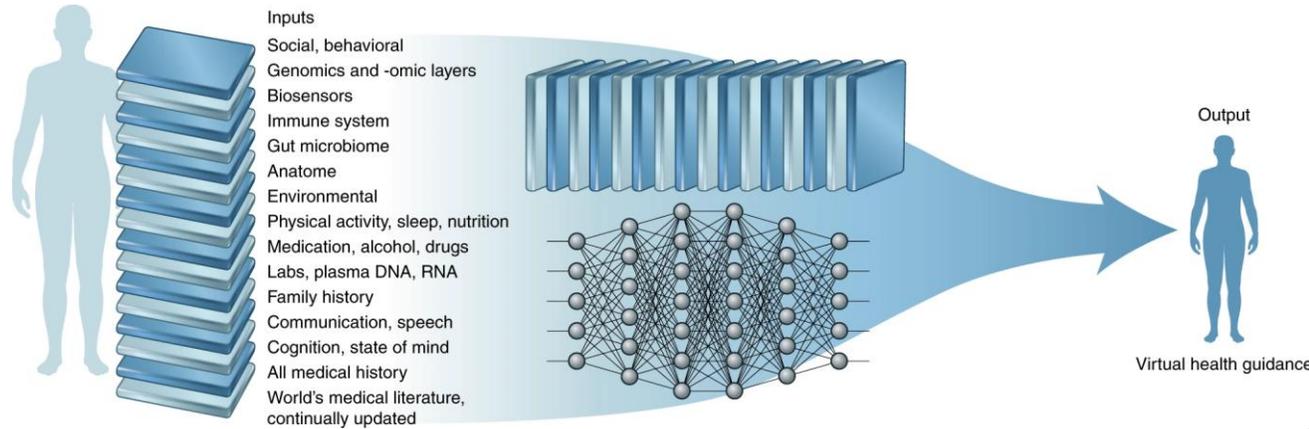


# AI as an active agent of biomedical discovery

Empowering biomedical discovery with AI agents

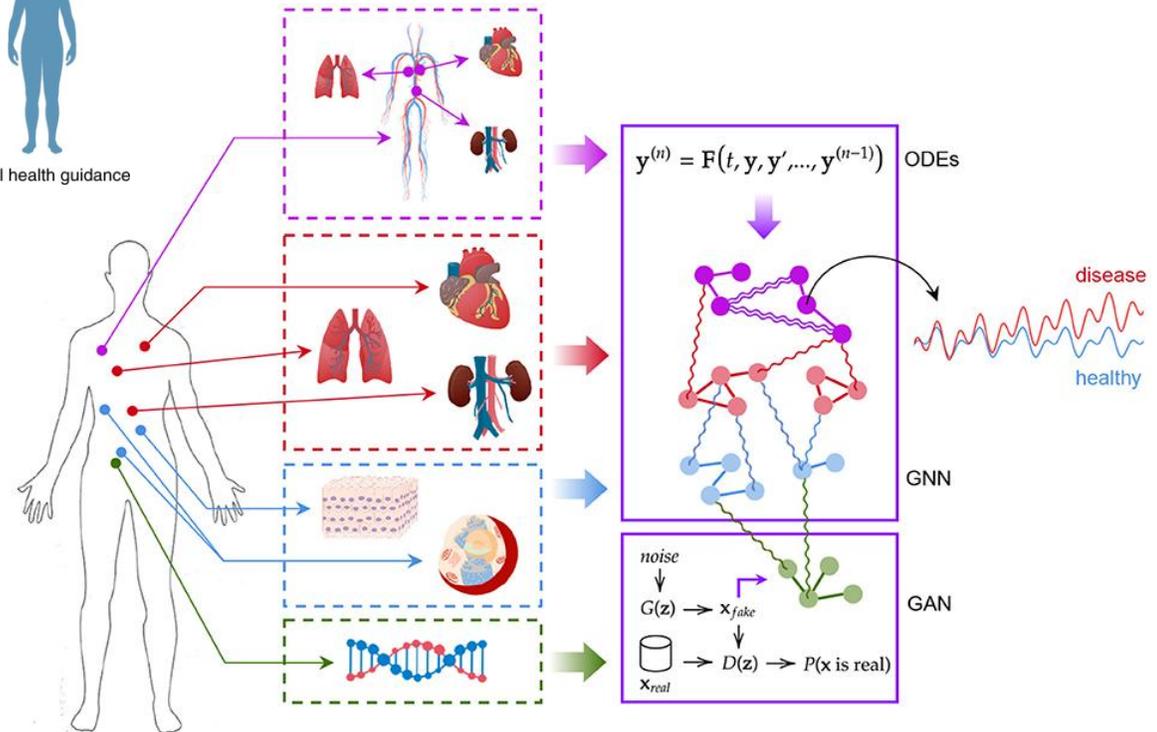


# Towards a multi-level and multi-systemic understanding of health



Topol, Nature Medicine 2019

Personalized **digital twins** modeling the human body as a whole and **providing a panoramic view over individuals' conditions**



Barbiero et al, Front. Genet.. 21

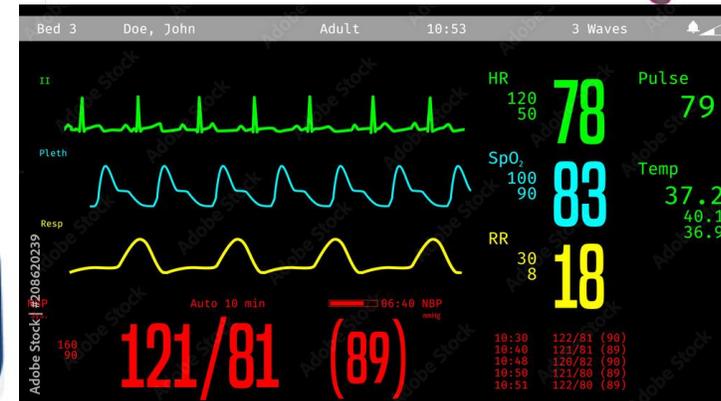
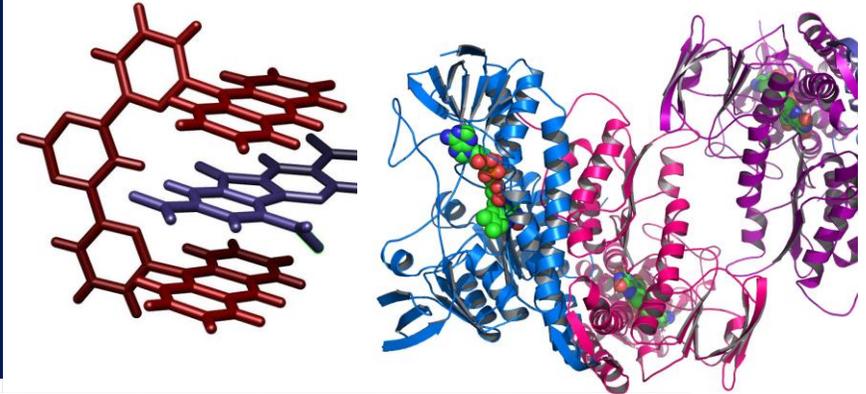
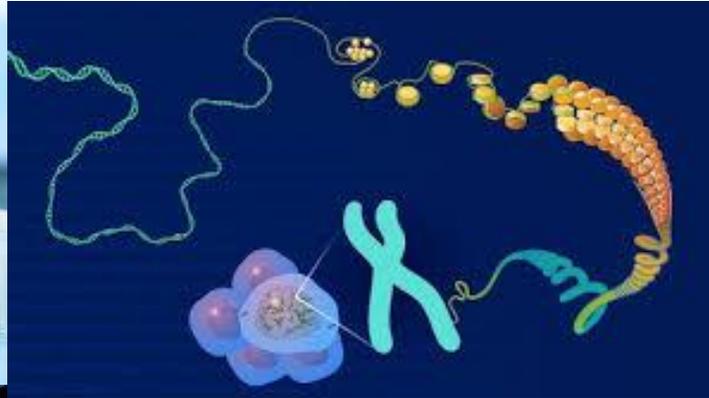
# Perks of biomedical/health applications

# Biomedical data

Complex

Multimodal

Heterogenous



Noisy

Biased and confounded

Long-tailed

# What makes AI for health so different?

- Many **questions are about unsupervised learning**
  - Discovering disease subtypes, or answering question such as “characterize the types of people that are highly likely to be readmitted to the hospital”?
- Many of the questions we want to answer are **causal**
  - Naive use of supervised machine learning is insufficient
  - Performative effects
  - Assessing the **impact of interventions**

# What makes AI for health so different?

- Very **little labeled** data
  - Recent breakthroughs in AI depended on lots of labeled data!
  - Motivates **semi-supervised and self-supervised** learning
- Sometimes **small numbers of samples** (e.g., a rare disease)
  - Learn as much as possible from other data (e.g., from healthy patients)
  - Model the problem carefully
- Lots of **missing data**, **varying time** intervals, **censored** labels

# Trust, ethics and legal aspects

- Life or death decisions
  - Accuracy alone is no longer enough
  - Need **robust**, **fair** and **accountable** methodologies
  - **Trustworthy AI** (focus of other courses)
- Difficulty of **de-identifying data**
  - Need for data sharing agreements and sensitivity
- Difficulty of **correcting for biases and inequities**
  - Consideration of ethical and legal issues
  - Health data on which algorithms are trained are likely to be influenced by many facets of social inequality
- **Rigorous testing** and validation are needed
  - Longer time-to-market of technologies

# Operational aspects

## Difficulty of deployment of data-driven solutions

- **Commercial** electronic health record software is difficult to modify
- Data are often in **siloes**; everyone recognizes need for interoperability, but slow progress

# Course execution and examination

# Key ingredients of this course

- Weekly lectures (2/3) – D. Bacciu
- Weekly lab tutorials (1/3) – M. Podda
- Monthly **laboratory assignment**: in-class, graded
- Monthly short **methodological quizzes**: in-class, graded

# Lectures

- Introduction of concepts, terminology, models and methodologies
- We will use mathematical formalisms to **introduce concepts, models and their inner workings** (yes this will be part of the oral exam)
- We will not indulge in mathematical demonstrations but favour understanding of the methodologies and their use

# Lab Tutorials

- Revisit and expand key concepts introduced in lectures with focus on their practical **implementation** and **usage**
- Mostly in **Python** with **Jupyter** notebooks (**Colab** preferably, but feel free to run your own notebooks locally)
- Prior knowledge of **numpy** and **pandas** is assumed from previous courses, but will be refreshed as we go by
- Will also leave some additional notebooks for home study
  - Optional, but still useful to complement the lectures

# Laboratory Assignments

- More involved exercises (30 min to 1 hour) **in-class**
- **1 every 4 lab lessons**
- Designed to test your understanding
- Work on them **on your own**
- Formal and **graded**, 0-3 points (see in a minute)
- Will publish a solution and grades in the following days

# Methodology Quizzes

- Monthly quizzes based on the content of the lectures of the period
- Will be **served in-class** and they will be **closed-book**
- Will be short, requiring **maximum 10 minutes** to be completed and performed “on paper” (electronic devices not allowed)
- Will be graded on completion: each **fully completed quiz scores 1 point** (fractions of the point are possible)

They will be **delivered at random lectures** and  
unannounced

# Course Assessment (Exams)

## Preferential way for full time students

- **Laboratory assignments** - A total of 4 laboratory assignments related to lab hands-on
- **Methodological quizzes** - A total of 4 laboratory assignments related to lecture content
- **Oral exam** – An examination on the course program

**Alternative way** (part-time students, those who fail or don't like the other way)

- **Final Project** – A coding project on a topic of interest for the course
- **Oral Exam** - A 15 minutes presentation of the final project plus examination on the course program

# Final Project

- A coding project on a topic of interest for the course (defined by the instructors)
- What to deliver
  - The code (not the data)
  - A 10 pages report describing the project methodology and its validation
  - A 10/15 slides presentation (that will be given on the oral day)
- Timeline
  - Final project topic published: [early May](#)
  - Project materials delivered on Moodle by the [exam date published on the esami platform](#) (strict)

# Oral Exam

- Give your presentation on the **final project** (15 minutes)
  - Discuss it in front of instructors and anybody interested
  - Questions on the methodology, validation and implementation
- An oral exam with **questions covering the course contents**
  - Questions on models, methodologies and their implementation
  - Lectures whose content is not relevant for the final exam will be clearly marked as such

Only for those  
who did not  
choose the  
preferential way

# Grading – The Preferential Way

- Laboratory assignments grade  $G_{lab}$ 
  - Each assignment is scored in  $[0,3]$
  - Total grade achievable  $G_{lab} = 12$  (since there are 4)
- Methodological quizzes grade  $G_{quiz}$ 
  - Each quiz is scored in  $[0,1]$
  - Total grade achievable  $G_{quiz} = 4$  (since there are 4)
- Students are admitted to the oral if  $G_{lab} + G_{quiz} > 8$
- Oral exam grade  $G_{oral}$  is scored in  $[0,18]$
- The final grade is  $\min(G_{lab} + G_{quiz} + G_{oral}, 30 \text{ Lode})$

# Grading – The Alternative Way

- Final project grade  $G_{prj}$  is scored in  $[0,30]$
- Oral exam grade  $G_{oral}$  is scored in  $[0,32]$
- The exam is passed if both  $G_{prj}$  and  $G_{oral}$  are at least 18
- The final grade is

$$\frac{G_{prj} + G_{oral}}{2}$$

# Policies

- You can collaborate with others, but we ask that you **write your solutions individually**
- We favor **in-person attendance to all classes**: preferential exam modality will support this
- We support use of genAI (LLMs, coding copilots, etc):
  - **Responsibility for content**: Students who use genAI in their assignments take full responsibility for the content they submit
  - **Acknowledgment of AI use**: Clearly acknowledge any use of genAI, specifying the nature and extent of assistance received from AI.
  - **Ethical use and originality**: Do not use AI to plagiarize, misrepresent original work, or fabricate data
  - **Instructor discretion**: We may specify assignments genAI use is prohibited

# Next Lecture

Fundamentals of probability and statistics for AI

- Refresher on Probability and Statistics
- Hypothesis Testing and Statistical Inference
- Statistical dependence
- Statistics for healthcare data