

Toepassingen van artificiële intelligentie in klinische laboratoria

KU LEUVEN

prof. apr. klin. biol. Glynis Frans
Dienst Laboratoriumgeneeskunde



- Introductie tot artificiële intelligentie
- Toepassingen in de klinische biologie
- Hoever staan we in de praktijk?
- Take home messages

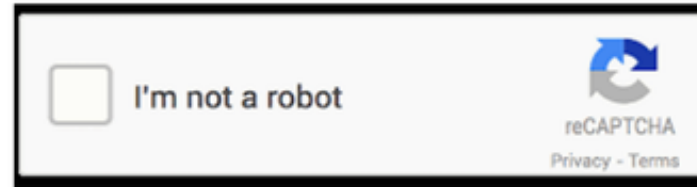
De term “artificiële intelligentie” dateert uit de jaren 1950.



Alan Turing

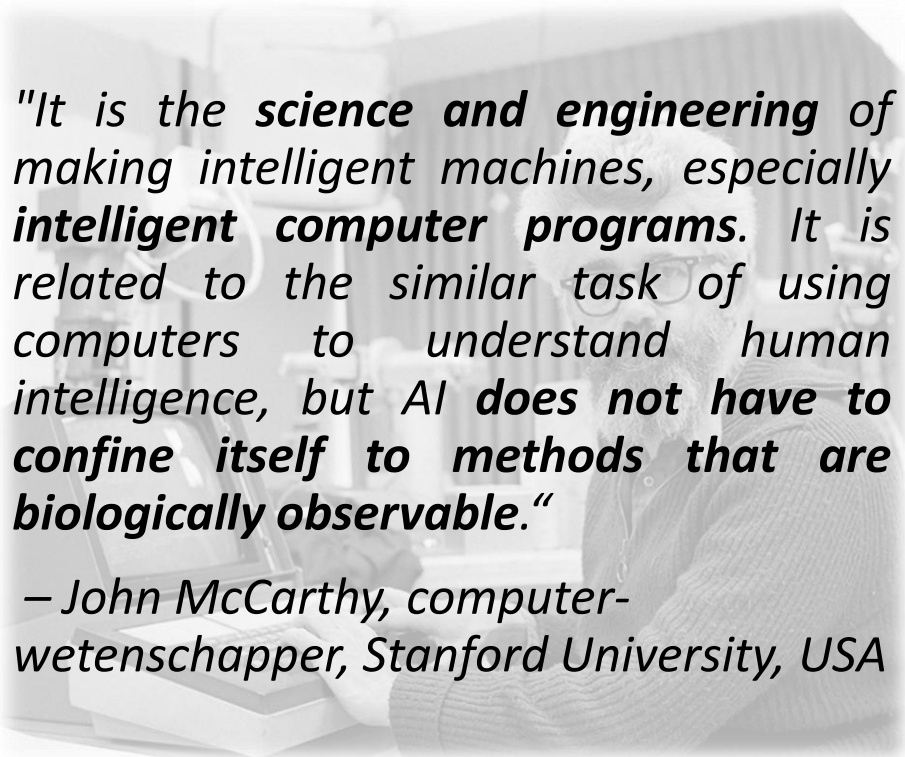
1950: Can a computer convince a human that it is not a computer but a real person.

Now: Can a human convince a computer that he is a real person, not a computer



Het baanbrekende werk van Alan Turing “*Computing Machinery and Intelligence*” beschreef onder meer de “Turing-test”.

Verskillende definities werden al voorgesteld...



*"It is the **science and engineering** of making intelligent machines, especially **intelligent computer programs**. It is related to the similar task of using computers to understand human intelligence, but AI **does not have to confine itself to methods that are biologically observable.**"*

– John McCarthy, computer-wetenschapper, Stanford University, USA

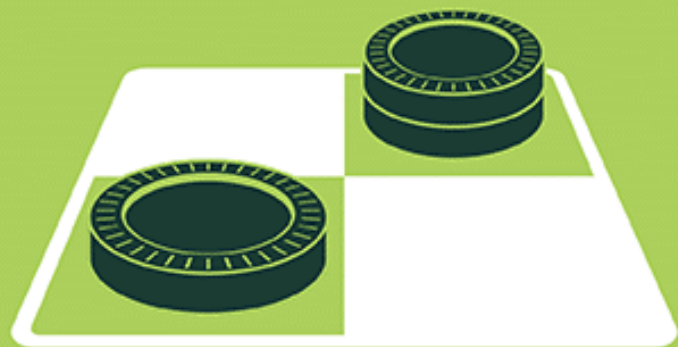


*"Software die goed is in **patroons-herkenning.**"*

- Lieven Scheire, wetenschapscommunicator, België

ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



MACHINE LEARNING

Machine learning begins to flourish.



DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's

1960's

1970's

1980's

1990's

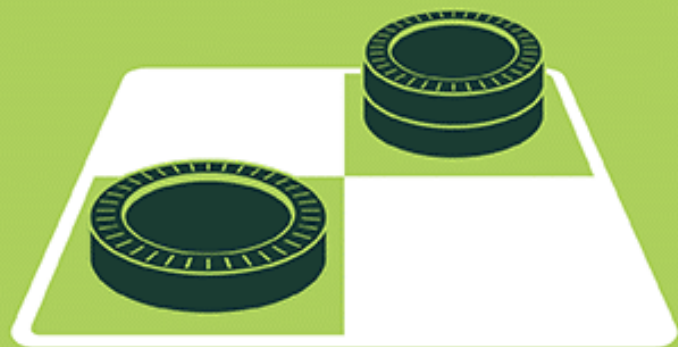
2000's

2010's

- De eerste vormen van AI verschijnen in **clinical decision support (CDS) systemen** die gebaseerd zijn op regels en een kennisdatabase.
- Medische validatieregels worden opgesteld, gecontroleerd en aangepast door experts (zoals klinisch biologen) om het redeneren van een menselijke specialist na te bootsen.
- Voorbeelden van medische validatieregels zijn:
 - als K hoger is dan 6,5 mmol/L → kritieke waarde, doorbelactie vereist.
 - als Hb meer dan X g/dL varieert → heranalyse vereist.
 - als Na binnen 24 uur met meer dan 10 mmol/L verandert → waarschuwing gegeven.

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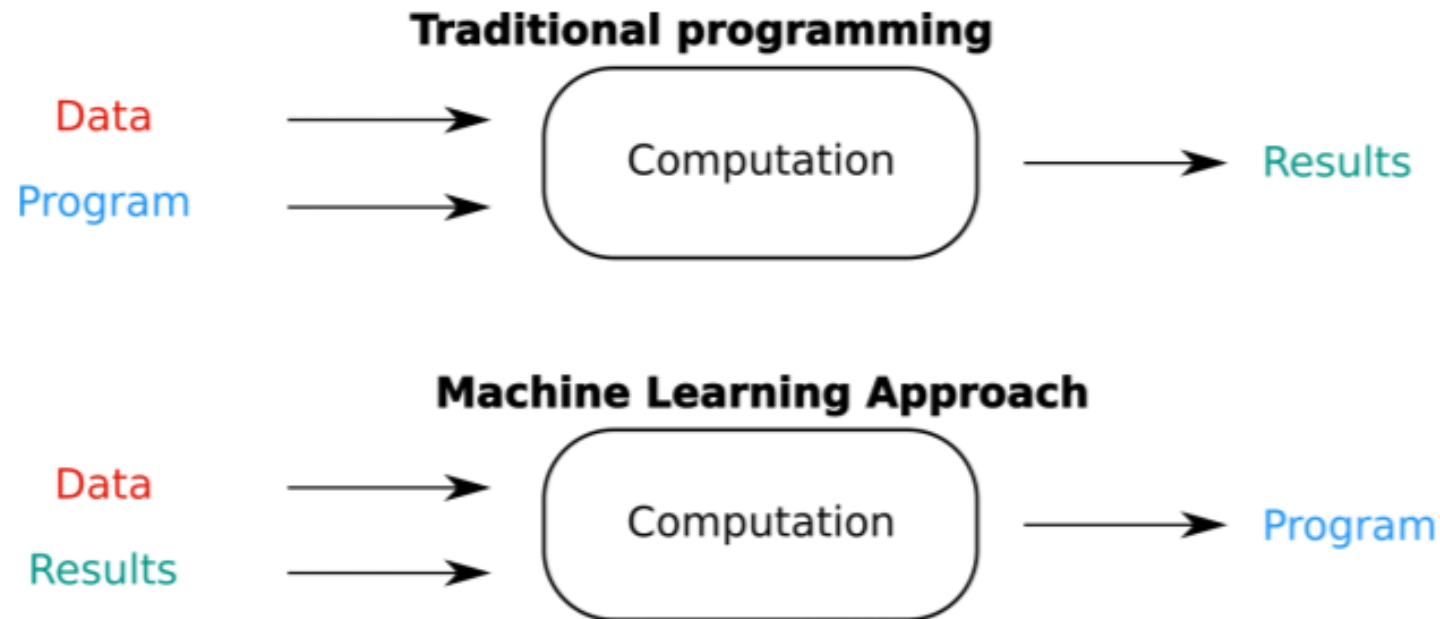
1990's

2000's

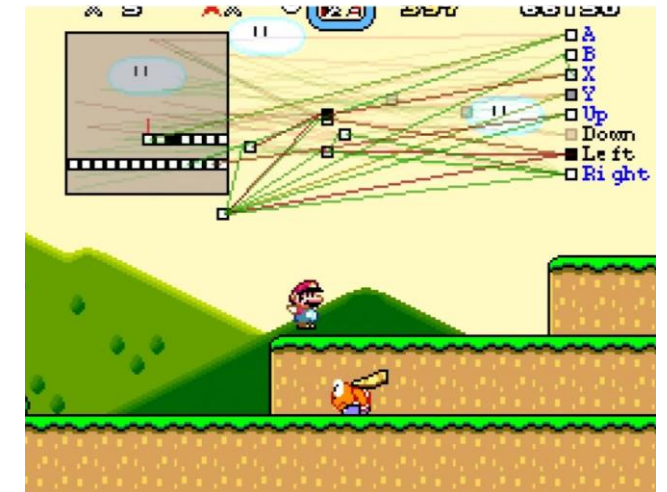
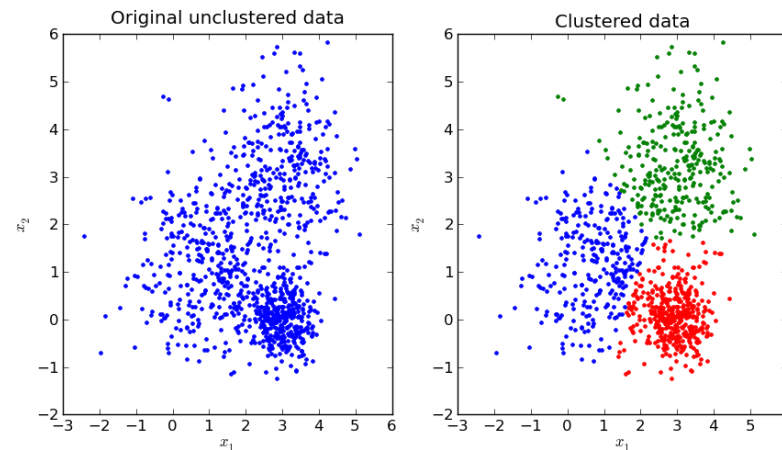
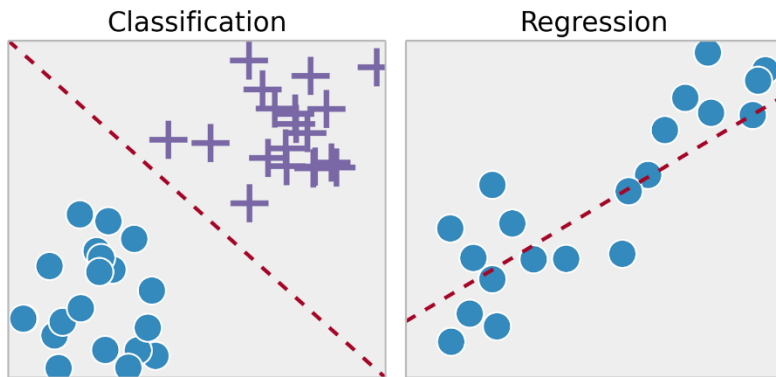
2010's

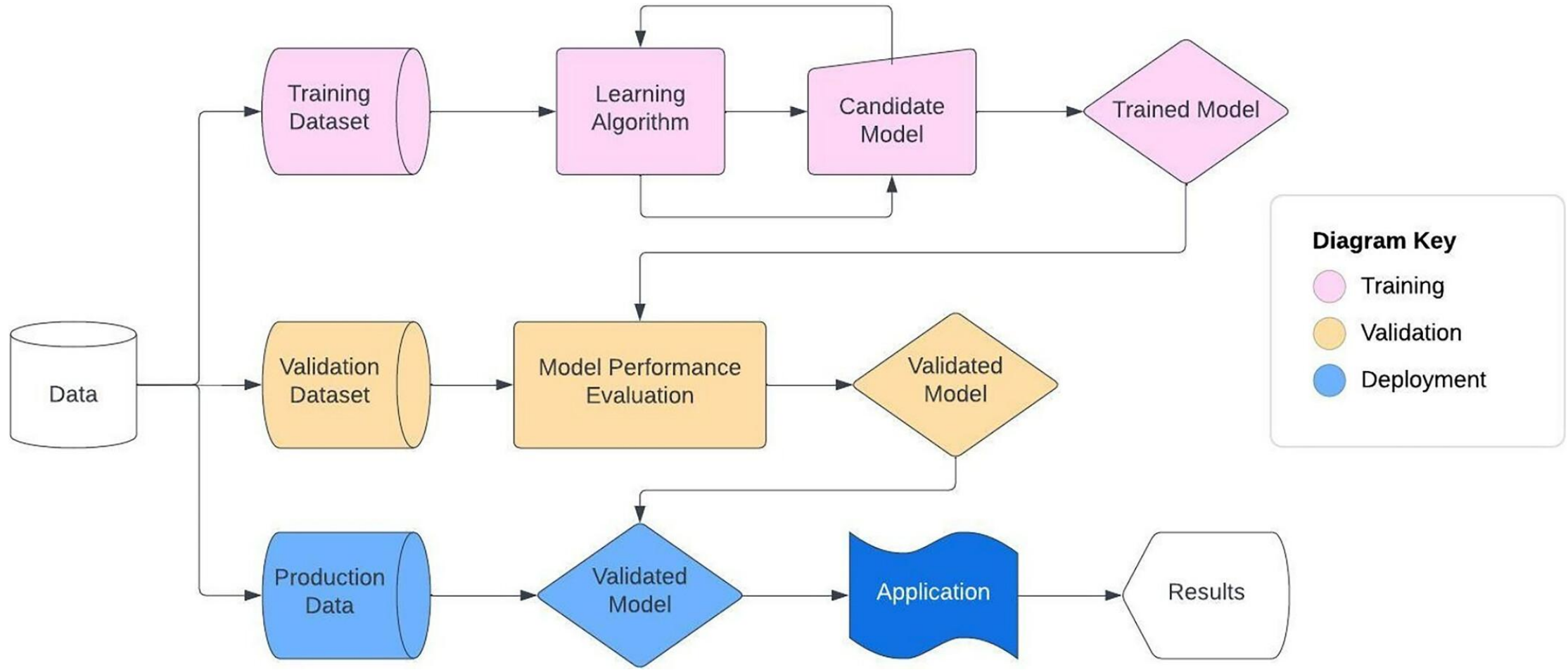
Machine learning

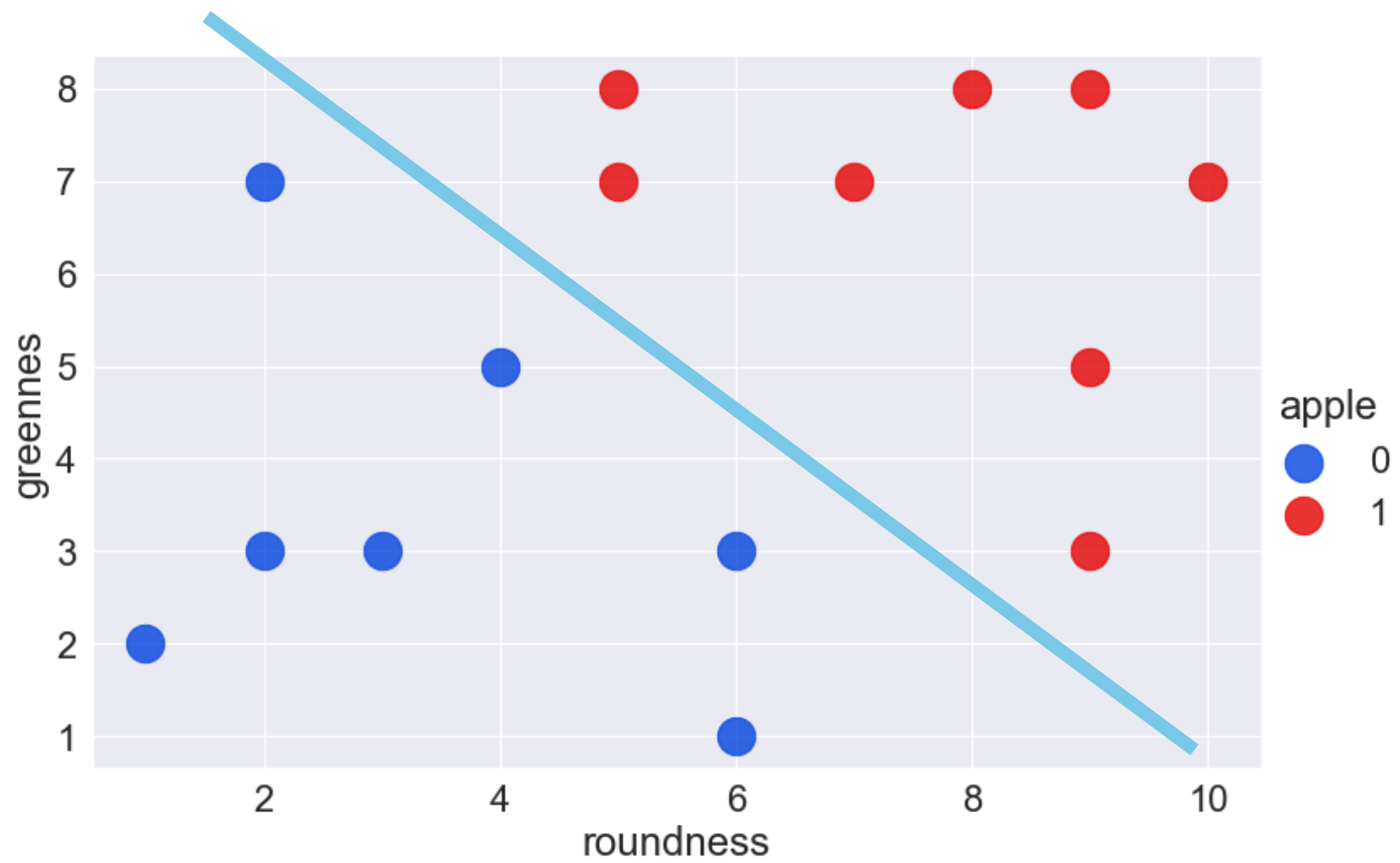
- ✓ Computers die leren van data om specifieke taken uit te voeren.
- ✓ Vaak ook “statistical learning” genoemd.
- ✓ Geen menselijke fouten/vooroordelen.

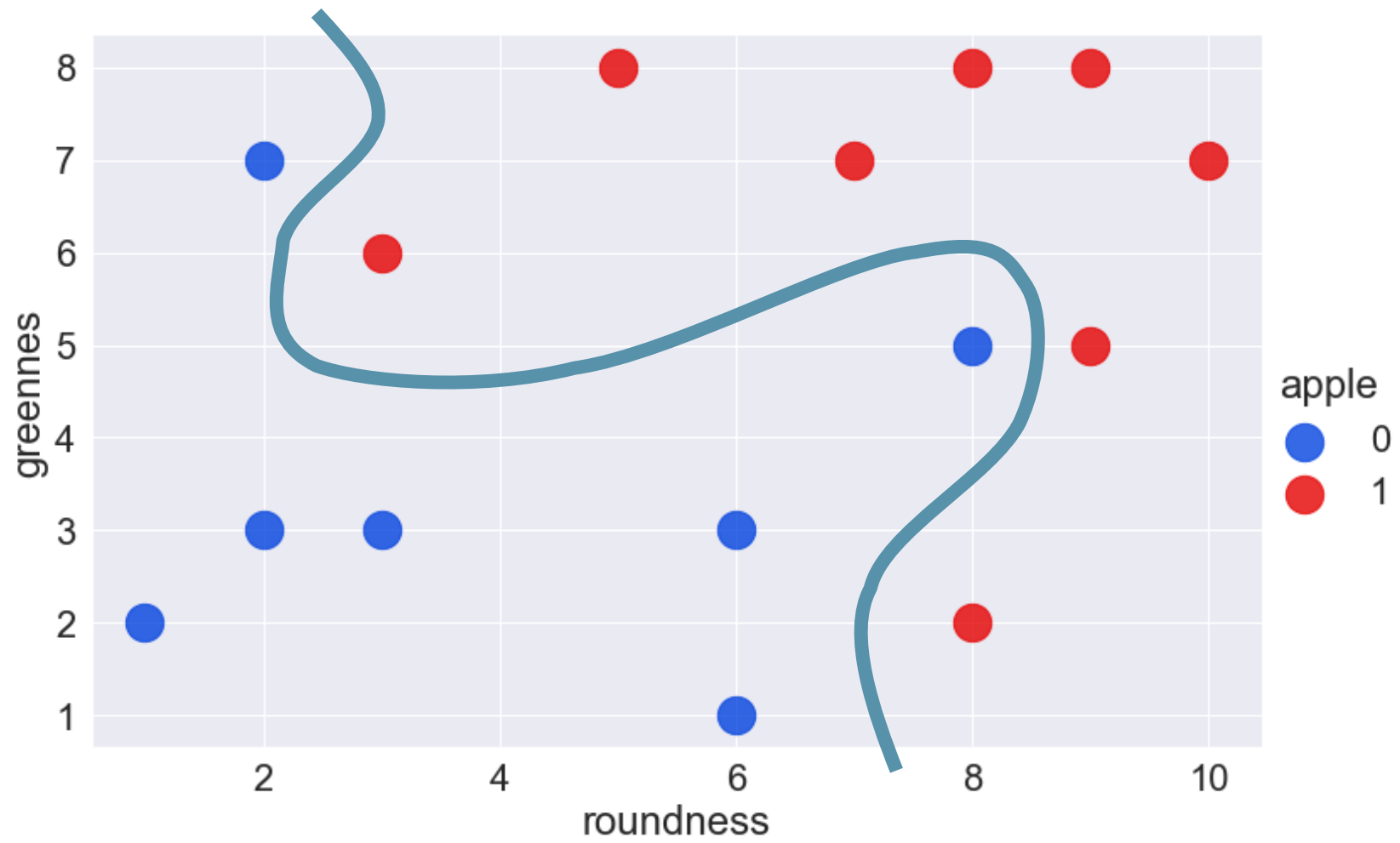


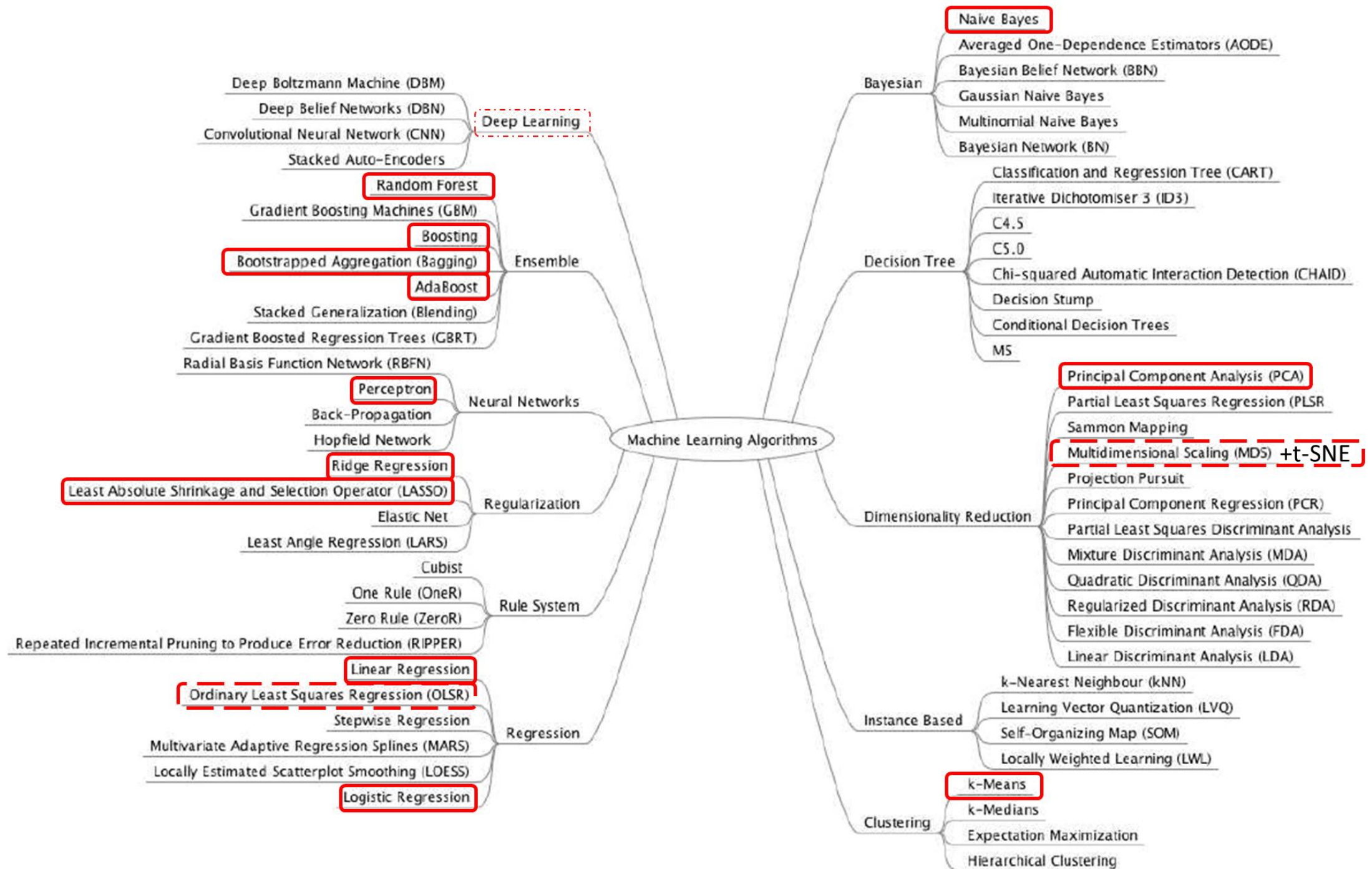
Supervised learning	Unsupervised learning	Reinforcement learning
Inputs en gewenste outputs zijn aangeleverd	Gewenste outputs zijn niet aangeleverd	Beslissingsproces gebaseerd op beloningen
Taakgericht	Datagedreven (clustering)	Algoritme leert reageren op zijn omgeving





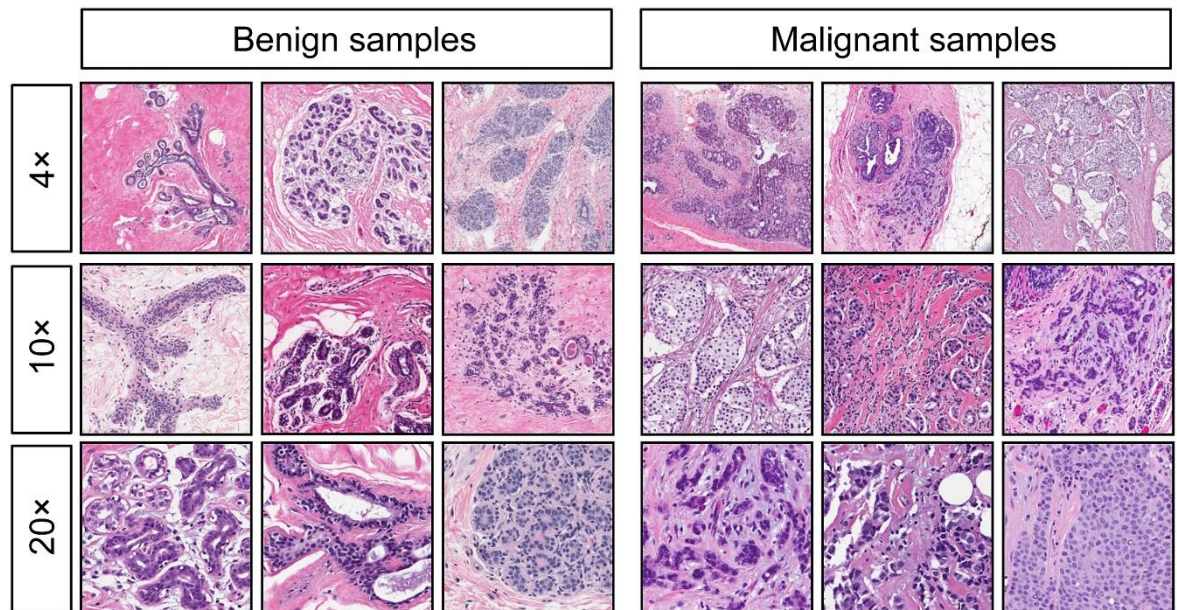






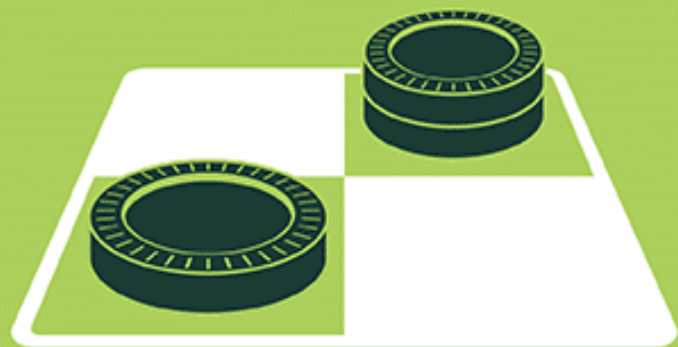
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	class
2	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
3	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
4	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
5	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
6	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	0	30	United-States	<=50K
7	34	Private	198693	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<=50K
8	29	?	227026	HS-grad	9	Never-married	?	Unmarried	Black	Male	0	0	40	United-States	<=50K
9	63	Self-emp-not-inc	104626	Prof-school	15	Married-civ-spouse	Prof-specialty	Husband	White	Male	3103	0	32	United-States	>50K
10	24	Private	369667	Some-college	10	Never-married	Other-service	Unmarried	White	Female	0	0	40	United-States	<=50K
11	55	Private	104996	7th-8th	4	Married-civ-spouse	Craft-repair	Husband	White	Male	0	0	10	United-States	<=50K
12	65	Private	184454	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	6418	0	40	United-States	>50K
13	36	Federal-gov	212465	Bachelors	13	Married-civ-spouse	Adm-clerical	Husband	White	Male	0	0	40	United-States	<=50K
14	26	Private	82091	HS-grad	9	Never-married	Adm-clerical	Not-in-family	White	Female	0	0	39	United-States	<=50K

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
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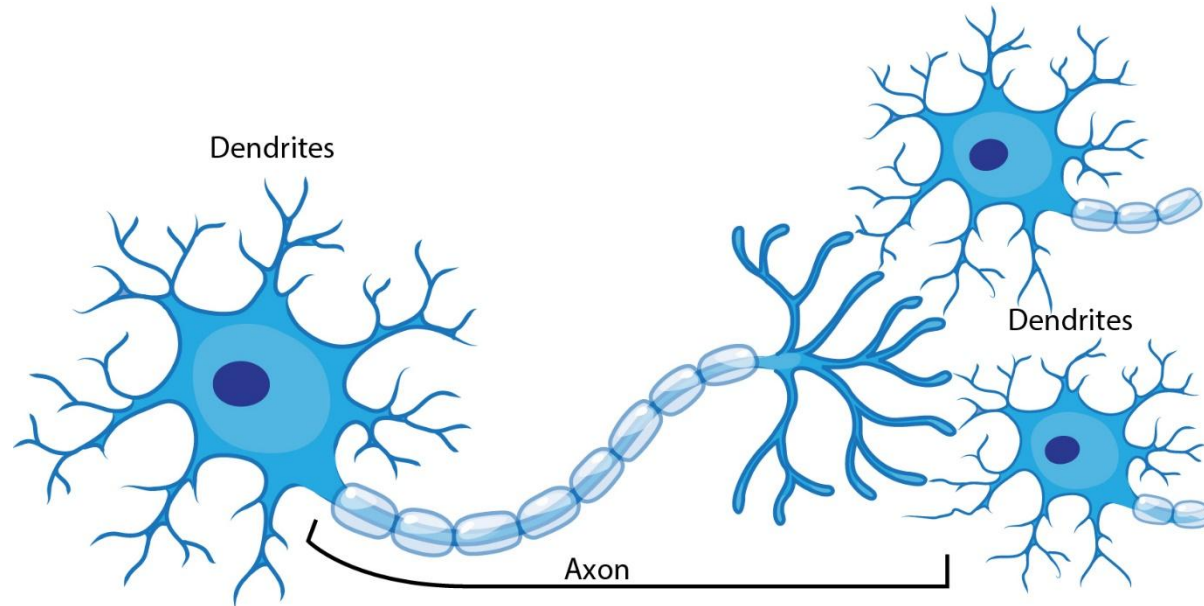
1990's

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2010's

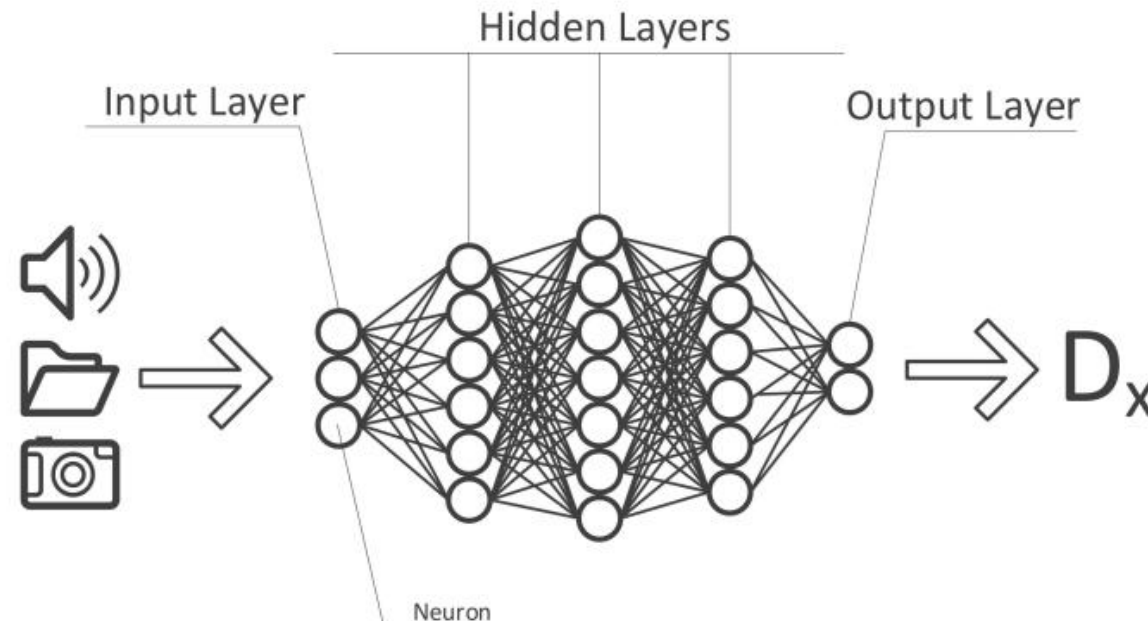
- Deep learning (DL) is een tak van machine learning die de functionaliteit ervan verbetert.
 - Het automatiseert het extraheren van variabelen en het optimaliseren van modellen (bv. hyperparameters afstellen).
 - Vermindert de behoefte aan menselijke tussenkomst en maakt het mogelijk om grotere datasets te verwerken.
- DL kan ongestructureerde, multimodale gegevens in hun oorspronkelijke vorm verwerken (bv. tekst, afbeeldingen en longitudinale data) en leert automatisch onderscheid te maken tussen verschillende categorieën.

Neurale netwerken, ook wel **artificiële neurale netwerken (ANN's)** genoemd, zijn een subset van machine learning en vormen de kern van deep learning-algoritmen. Hun naam en structuur zijn geïnspireerd door de menselijke hersenen en bootsen de manier na waarop biologische neuronen signalen doorgeven.



Artificiële neurale netwerken (ANN) \approx menselijk brein en neuronen.

- **Inputlaag:** waarden tussen 0 en 1, die de “activatie” van een neuron weerspiegelen.
- **Verborgene lagen:** wegen kenmerken van de inputdata van laag tot laag.
- **Outputlaag:** presenteert een voorspelling, gecombineerd met een waarschijnlijkheid.

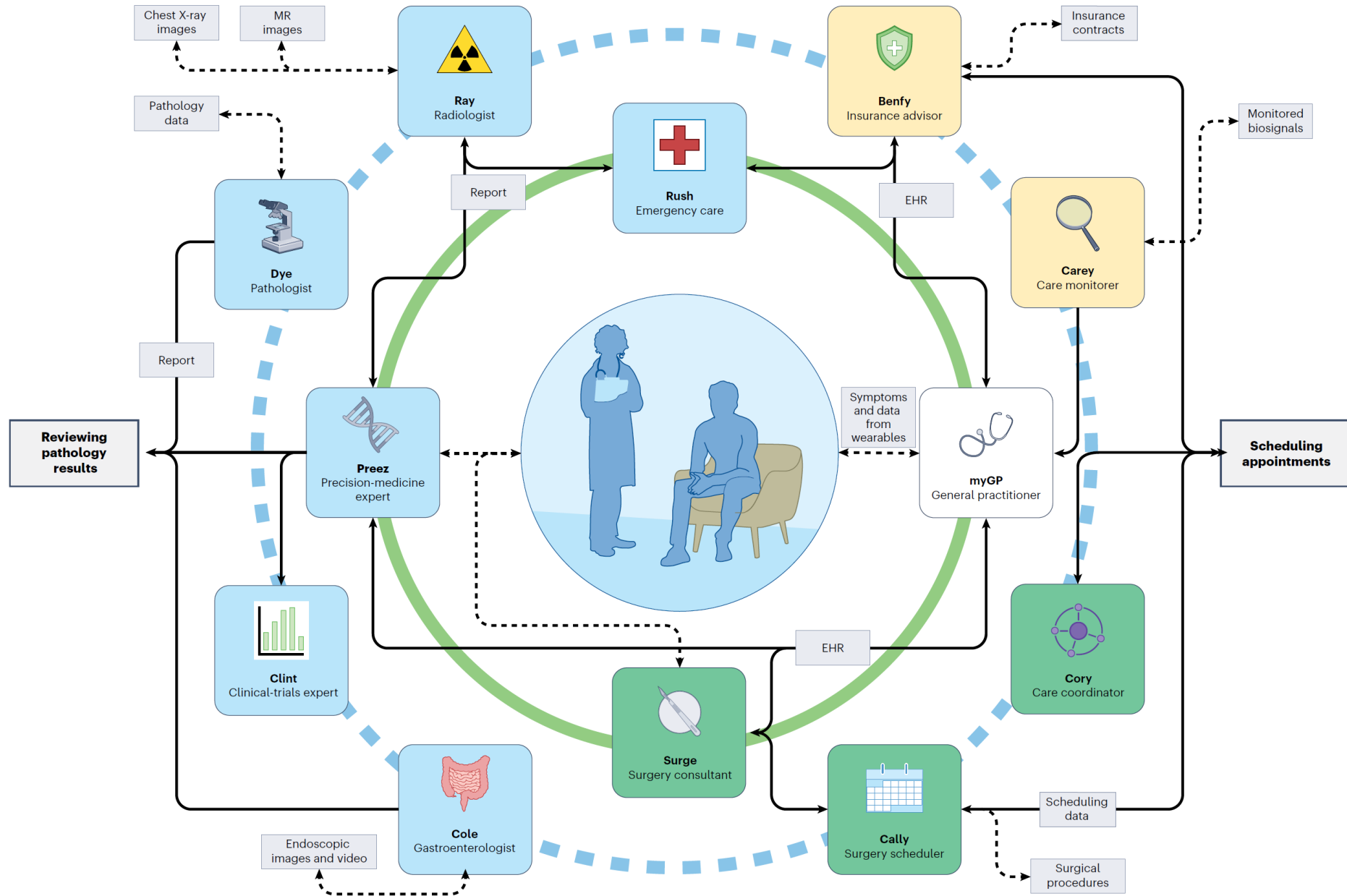


Definition

Learns the probabilities of occurrence of sequences of words from a corpus of text, whose probabilities are learned using textual corpora with trillions of words such that the resulting model has billions of parameters.

- Vorm van DL (neuraal network gecombineerd met een “transformer”), gebaseerd op “self-supervised learning”.
- Vaak geïntegreerd in chatbots.
- Kunnen worden afgestemd (“getuned”) op verschillende toepassingen.





Toepassingen in de klinische biologie

Anamnese

Klinisch
onderzoek

Medicatie

Laboratorium
resultaten



Voor-
geschiedenis

Sociale
achtergrond

Pathologie
resultaten

Beeldvorming
resultaten

Anamnese

Klinisch
onderzoek

Medicatie

Laboratorium
resultaten



Voor-
geschiedenis

Sociale
achtergrond

Pathologie
resultaten

Beeldvorming
resultaten

Pre-analytische fouten



Article

Analyte Importance Analysis in Machine Learning-Based Detection of Wrong-Blood-in-Tube Errors Using Complete Blood Count Data

Baş Gün Sürmeli ^{1,*}, René Staritzbichler ^{2,†}, Clemens Ringel ², Saleem Al-Dakkak ², Helene Dörksen ¹ and Thorsten Kaiser ²

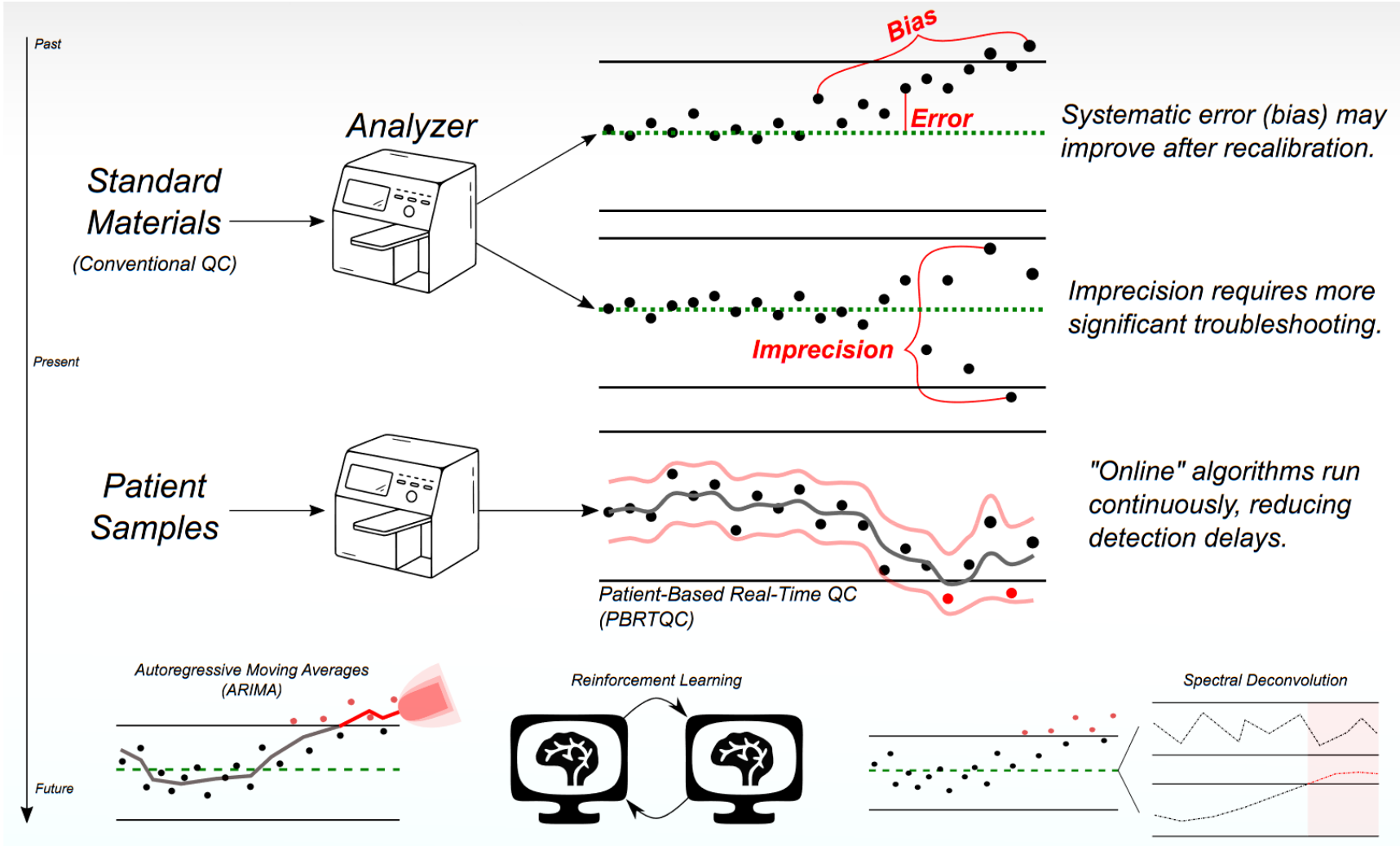
J. Pers. Med. **2025**, *15*, 404

<https://doi.org/10.3390/jpm15090404>

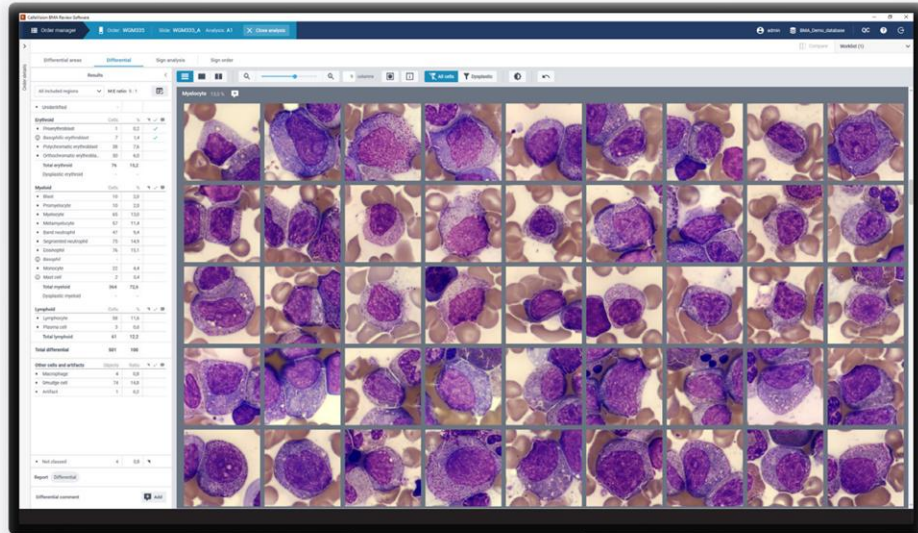
Prospective and External Validation of an Ensemble Learning Approach to Sensitive Detect Intravenous Fluid Contamination in Basic Metabolic Panels

Nicholas C. Spies ¹, Leah Militello ^d, Christopher W. Farnsworth ^a, Joe M. El-Khoury ^d, Thomas J.S. Durant ^d and Mark A. Zaydman ^a

Kwaliteitscontrole



Hematologie



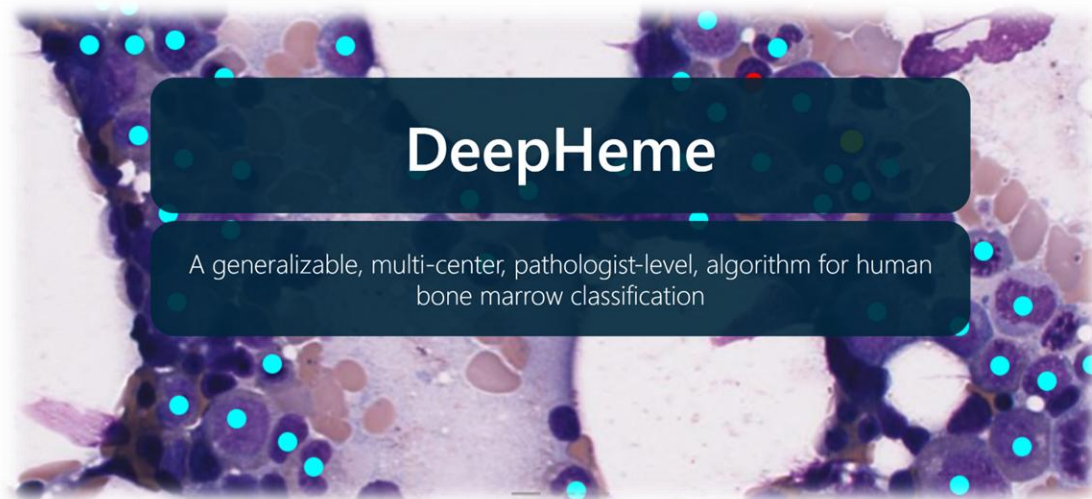
CELLAVISION



Scopio

DeepHeme

A generalizable, multi-center, pathologist-level, algorithm for human bone marrow classification

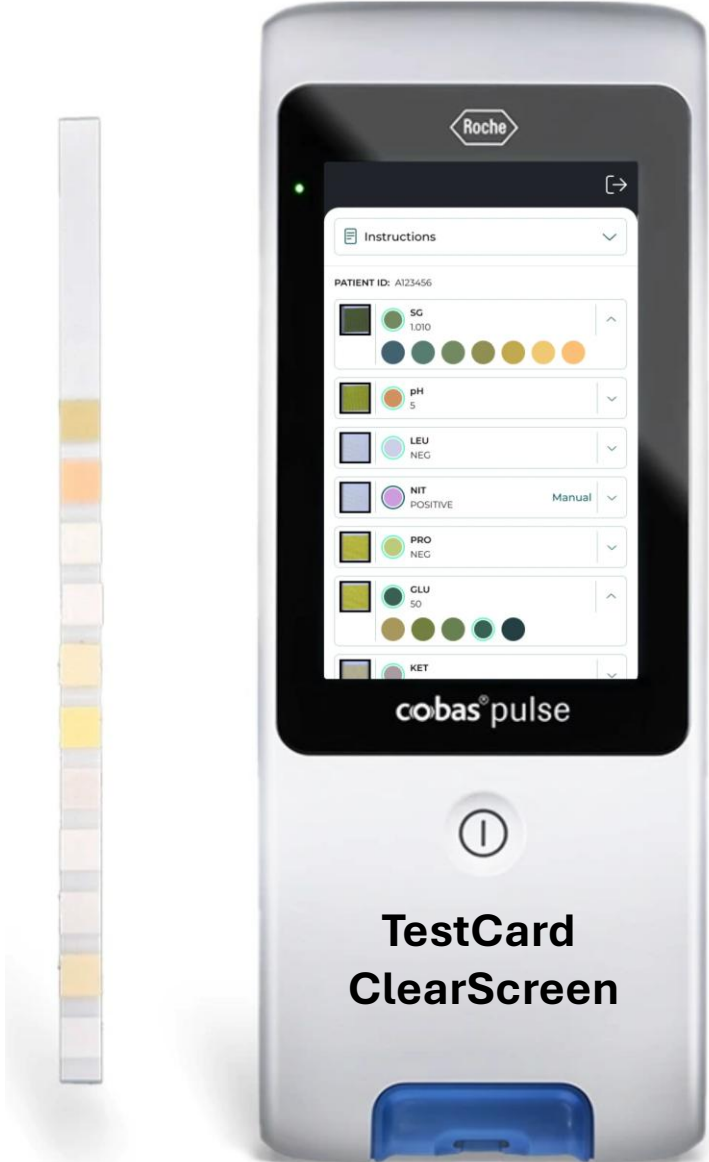


<https://www.hemepath.ai/deepheme.html>

<https://scopiolabs.com/>

<https://www.cellavision.com/>

Urine analyse



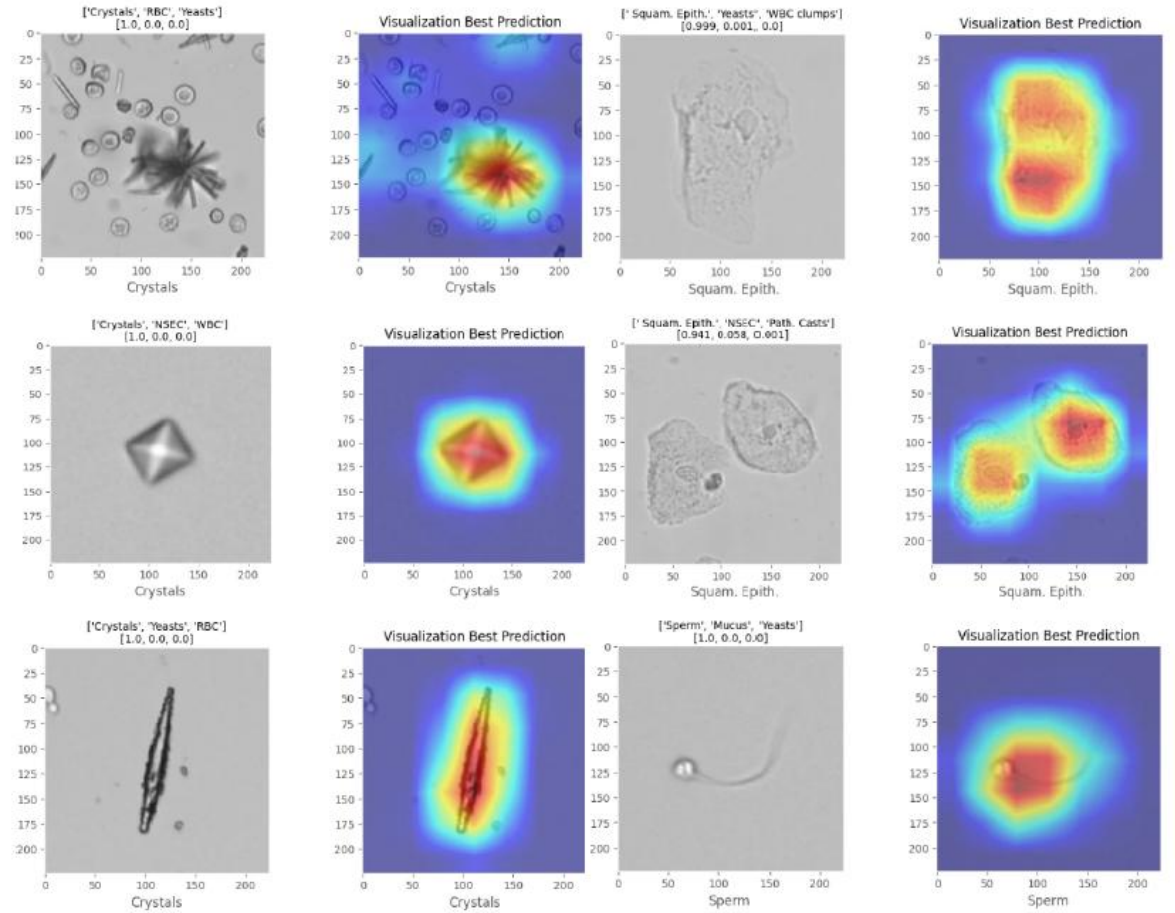
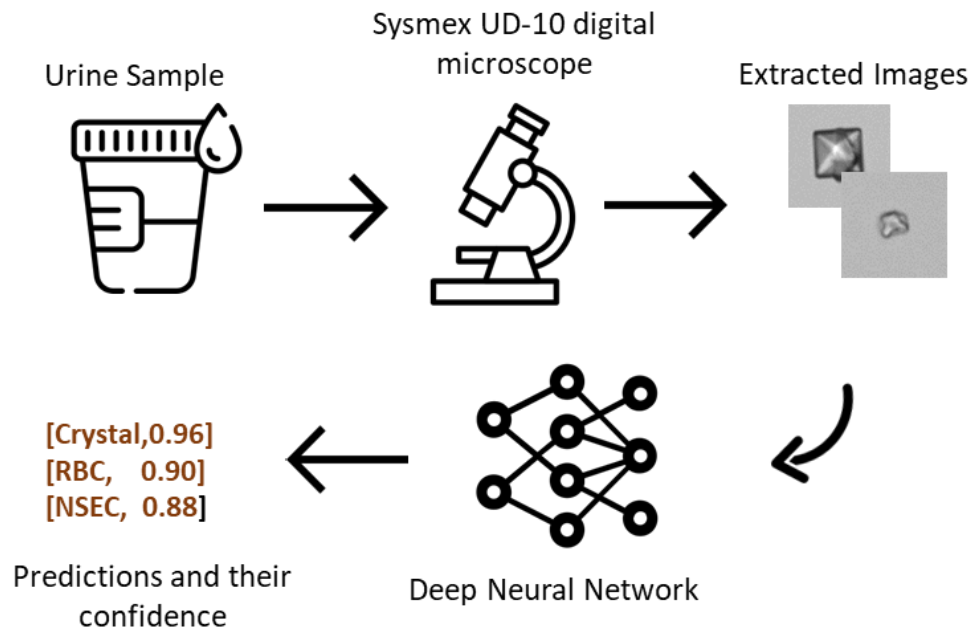
Inside Minuteful Kidney

Inside Minuteful Kidney you will find a urine collection cup, a single wrapped dipstick and a Color-Board, all waiting to help you take care of your kidney health.

Albumin-to-creatinine ratio

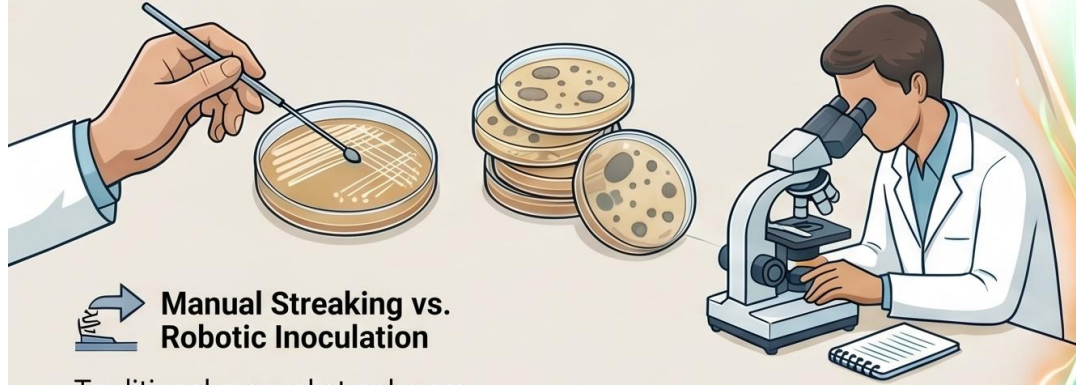
 Healthy.io

Urine analyse



Microbiologie

MANUAL WORKFLOW: Slow, Labor-Intensive, Subjective



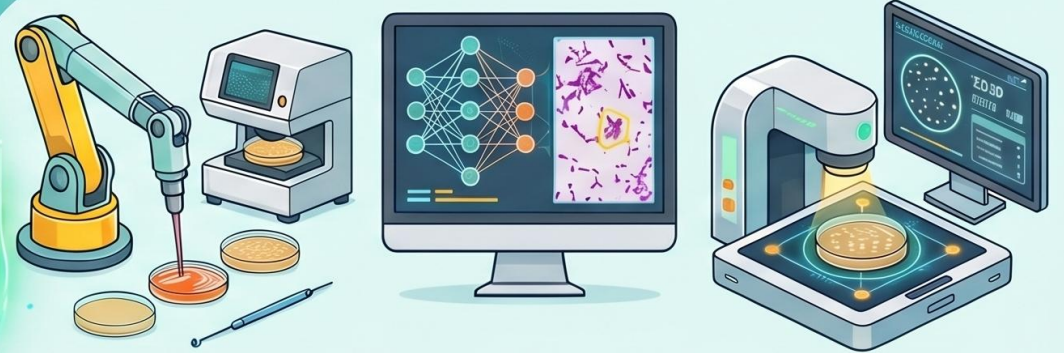
Manual Streaking vs. Robotic Inoculation

Traditional manual streaks are replaced by robotic streakers and AI-optimized inoculation strategies.

Manual Colony Counting & Identification:

Time-consuming visual inspection, prone to error.

AI-AUGMENTED WORKFLOW: Rapid, Data-Driven, High-Precision



95% Accuracy in Slide Interpretation

Convolutional robot-antix-axis precisely inoculation with laser-guided precision.

Convolutional Neural Networks (CNNs) classify Gram stain morphologies with high precision on standard computers.

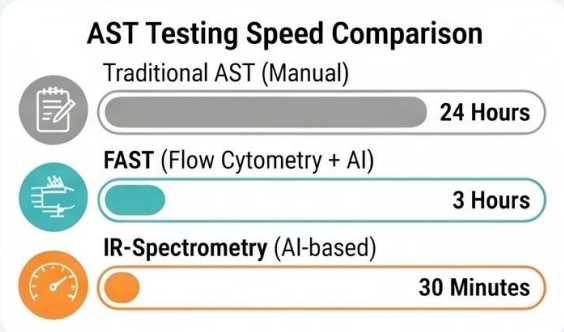
Real-Time "Smart" Plate Reading

Computer vision software automates colony counting and identification, reducing result times by hours.

ACCELERATING THE FIGHT AGAINST RESISTANCE (AMR)

24 Hours
30 MINUTES
24 Hours Reduced to 30 Minutes
AI-integrated IR-spectrometry identifies antimicrobial resistance in minutes rather than days.

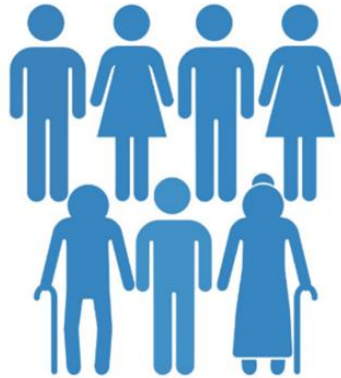
Predictive Resistance Modeling
ML algorithms analyze bacterial genomes to forecast drug resistance before physical tests finish.



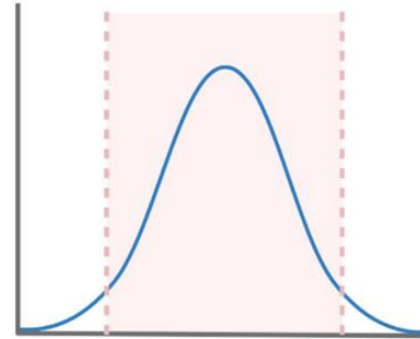
Smart molecule library
Virtual Drug Screening
Deep learning narrows thousands of molecules to viable drug candidates, saving time and resources.

Referentiewaarden

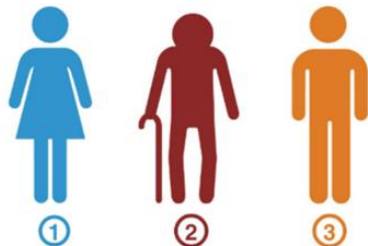
(A) Population-based Reference Interval



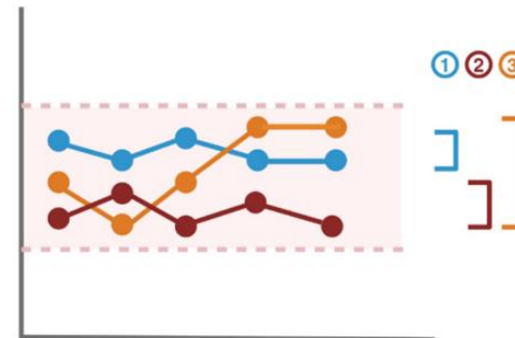
Determined by a one-time measurement, is used for every individual in the population.



(B) Personalized Reference Interval



Determined by longitudinal data from multiple measurements over time, and is to be used for that specific individual.



Risico inschatting

nature communications



Article

<https://doi.org/10.1038/s41467-025-66947-7>

Machine learning for risk stratification in the emergency department (MARS-ED): a randomized controlled trial

RISK^{INDEX}

- Risicoscore afgeleid van machine learning (ML).
- Voorspelt de kans op overlijden binnen 31 dagen door alle oorzaken, gebaseerd op routinematige laboratoriumtests die door de behandelend arts zijn aangevraagd, samen met basiskenmerken van de patiënt (leeftijd en geslacht).
- De berekende RISK^{INDEX} (waarde 0–100) komt overeen met de individuele waarschijnlijkheid van overlijden binnen 31 dagen.

Table 2 | Questionnaires regarding clinical intuition and medical treatment changes

Questionnaire regarding clinical intuition (intervention group and control group)

- Surprise question: "Would you be surprised if this patient dies within the next 31 days?" (yes/no)^{37,38}
- Concern question: "How concerned are you about the health of this patient?" (Likert scale 1-10)³⁹
- Severity question: "How severely ill do you find this patient?" (Likert scale 1-10)⁴⁰

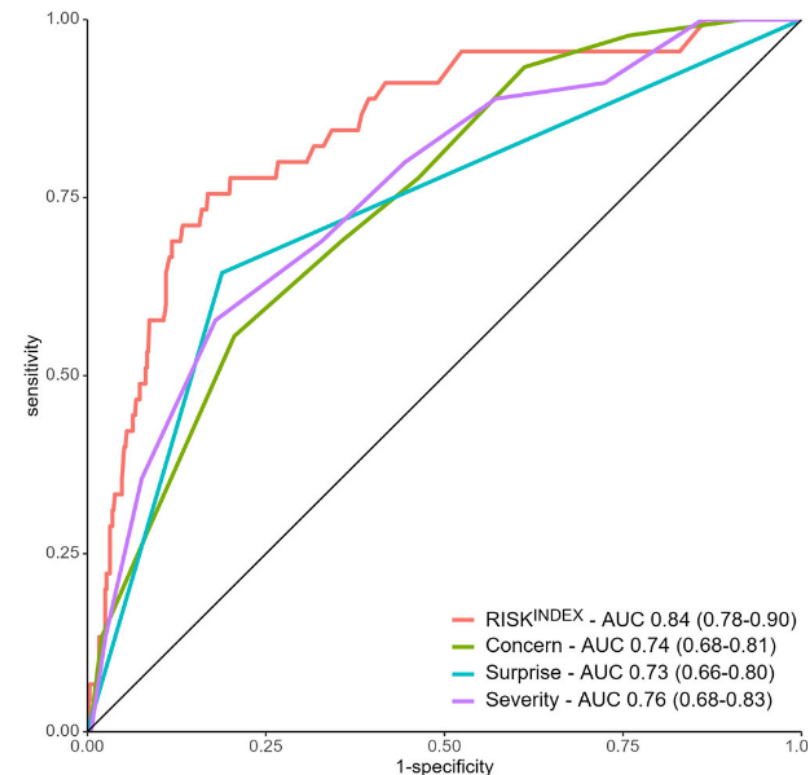


Fig. 2 | Prognostic accuracy for 31-day mortality of the RISK^{INDEX} compared with the ED physician's clinical intuition. The RISK^{INDEX} demonstrated high prognostic accuracy, achieving an area under the receiver operating characteristics curve (AUROC) of 0.84 (95% CI: 0.78–0.90). This statistically matched or outperformed that of the ED physician's clinical intuition, assessed through three distinct questions: the "concern" question showed an AUROC of 0.74 (95% CI 0.68–0.81, $p = 0.017$), the "severity" question an AUROC of 0.76 (95% CI 0.68–0.83, $p = 0.05$), and the "surprise" question an AUROC of 0.73 (95% CI 0.66–0.80, $p = 0.007$). The AUROCs were compared by using the method of DeLong.

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- De berekende RISK^{INDEX} (waarde 0–100) komt overeen met de individuele waarschijnlijkheid van overlijden binnen 31 dagen.

Supplementary Figure 5. Subanalysis of the perceived added value of the RISK^{INDEX} (Likert scale 1-10).

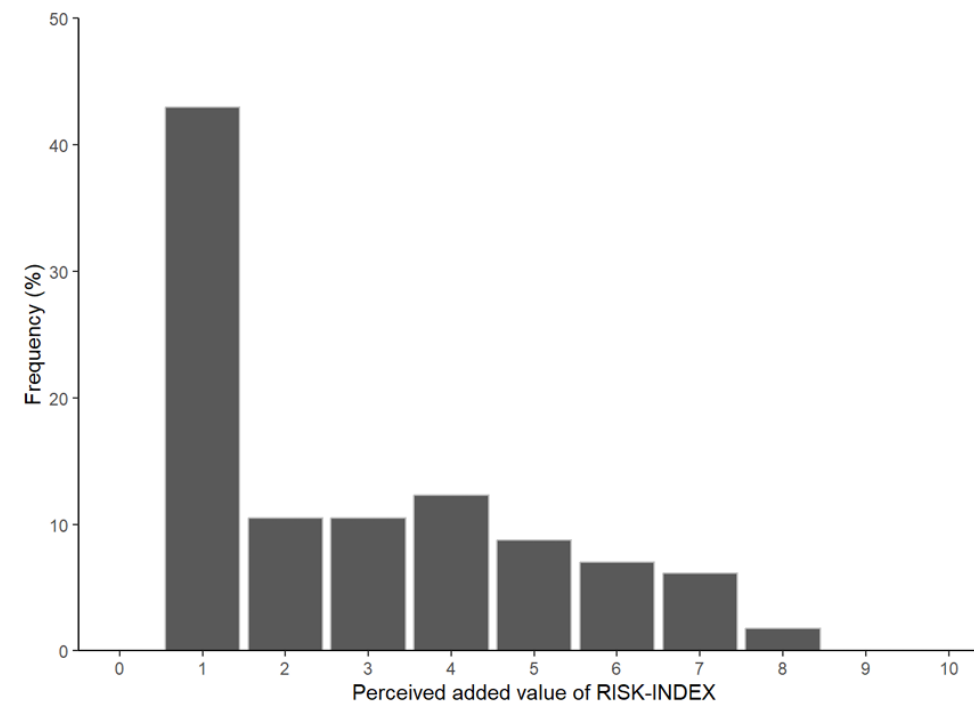


Table 1 | Characteristics of the study sample

	Intervention (n = 644)	Control (n = 659)	Overall (n = 1303)
Outcomes, n%			
Admission to hospital	400 (62.1)	414 (62.8)	814 (62.5)
Length of hospital stay, median (IQR), days	5 (2–9)	5 (2–9)	5 (2–9)
New treatment restrictions	86 (13.4)	71 (10.8)	157 (12.0)
Mortality (31-day)	45 (7.0)	45 (6.8)	90 (6.9)
ICU admission (31-day)	16 (2.5)	20 (3.0)	36 (2.8)

Generatieve AI



Clin Chem Lab Med 2023; aop

Janne Cadamuro, Federico Cabitza, Zeljko Debeljak, Sander De Bruyne, Glynis Frans, Salomon Martin Perez, Habib Ozdemir, Alexander Toliros, Anna Carobene and Andrea Padoan*

Potentials and pitfalls of ChatGPT and natural-language artificial intelligence models for the understanding of laboratory medicine test results. An assessment by the European Federation of Clinical Chemistry and Laboratory Medicine (EFLM) Working Group on Artificial Intelligence (WG-AI)

“Act as a **personal assistant who is a laboratory medicine expert** and can interpret lab exam results and help patients understand them. I will give you a **list of test results, their unit of measure, reference intervals, and relevant information about the individual, such as age and sex**. In particular, the result pattern will be the following one: “Test Name (unit of measure): Test Result (Reference range)”. Your task is to **interpret** these results both collectively and individually to inform the person, and **raise alerts** if values are out of normal ranges and advice for a referral if this is the case. Be as evidence-based as possible. If you are unable to interpret the results, or a single result, simply acknowledge that. If you recommend that the person consults a medical doctor, explain your reasoning for doing so. I report the case in what follows:”



Here's a summary and interpretation of the provided lab exam results for a 58-year-old male:

1. Red blood cell count, MCV, MCH, MCHC, Hb, and Hct: All of these values are within their respective reference ranges. This suggests that there are no issues with the patient's red blood cells or hemoglobin levels.
2. Platelet Count: This value is also within the reference range, indicating a normal platelet count.
3. White blood cell count: The total WBC count, as well as the counts for lymphocytes, neutrophil granulocytes, eosinophil granulocytes, basophil granulocytes, and monocytes, are all within their respective reference ranges. This indicates that there are no abnormalities with the patient's immune system based on these results.
4. Gamma-GT: This liver enzyme is within the normal range.
5. Glucose: The glucose level is elevated at 8.6 mmol/L (reference range: 3.88-5.55 mmol/L). This could be a sign of prediabetes or diabetes. Further evaluation and monitoring are recommended.
6. Total Cholesterol, HDL-Cholesterol, LDL-Cholesterol, and Triglycerides: All lipid levels are within their respective reference ranges, suggesting a healthy lipid profile.
7. Creatinine: The creatinine level is slightly elevated at 108 $\mu\text{mol/L}$ (reference range: 53-106 $\mu\text{mol/L}$). This may indicate a mild decrease in kidney function. However, it is important to consider other factors like muscle mass and hydration status when interpreting this result. Further evaluation might be necessary.
8. HbA1c: The HbA1c level is elevated at 57 mmol/mol (reference range: 20-42 mmol/mol). This suggests poor blood sugar control over the past 2-3 months and is consistent with a diagnosis of diabetes.

In summary, this individual has elevated glucose and HbA1c levels, suggesting a diagnosis of diabetes. The slightly elevated creatinine level may also warrant further investigation. It is important for the patient to consult with a medical doctor to discuss these findings, establish a diagnosis, and develop a management plan for diabetes and any potential kidney function issues.

Table 3: Summary of the findings of EFLM WG-AI members, listed as pros and cons.

Pros:

- All the lab tests provided were known and commented on (high relevance)
- Always recommend to check back with a doctor (high safety)
- Never recommends treatment options
- In one case a diabetes was identified correctly
- Good teaser for laymen to get familiar with laboratory medicine and life science in general

Cons:

- The underlying cause for result deviations is not always fully correct (e.g. GGT elevation=liver dysfunction or injury) (medium correctness)
 - Does not differentiate between slightly and severely deviated results (low safety in alert results)
 - Does not synoptically evaluate and interpret results (low helpfulness)
 - Does not take preanalytical issues into account
 - Does not recommend any follow-up diagnostics
 - Some answers were misleading (e.g. normal lymphocytes=normal immune system)
-

**Waar staan we in de
praktijk?**

Opinion Paper

Janne Cadamuro*, Anna Carobene, Federico Cabitza, Zeljko Debeljak, Sander De Bruyne, William van Doorn, Elias Johannes, Glynis Frans, Habib Özdemir, Salomon Martin Perez, Daniel Rajdl, Alexander Tolios and Andrea Padoan, on behalf of the European Federation of Clinical Chemistry and Laboratory Medicine Working Group on Artificial Intelligence

A comprehensive survey of artificial intelligence adoption in European laboratory medicine: current utilization and prospects

Deelnemers

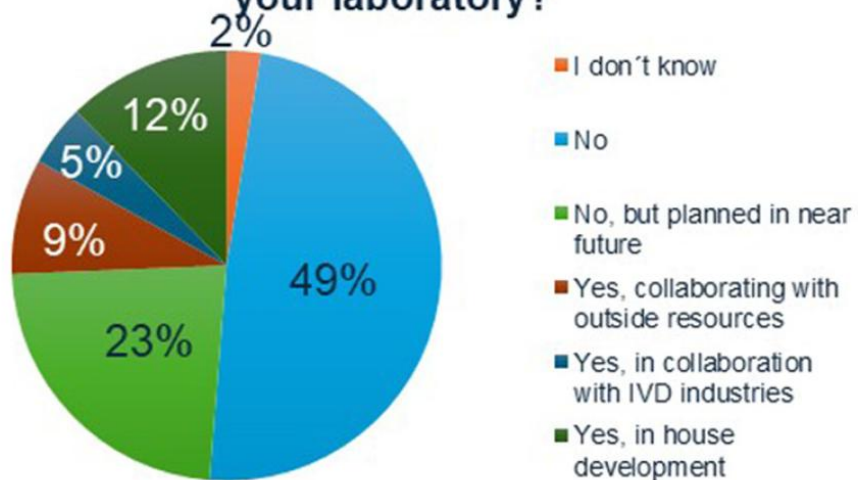
- Oktober 2023
- EFLM-mailing naar leden van nationale verenigingen
- Eén formulier per laboratorium

- 426 reacties -> 195 volledige antwoorden
 - 211 = onvolledig
 - 11 = reactie uit niet-Europees land
 - 9 = reactie niet uit een klinisch laboratorium

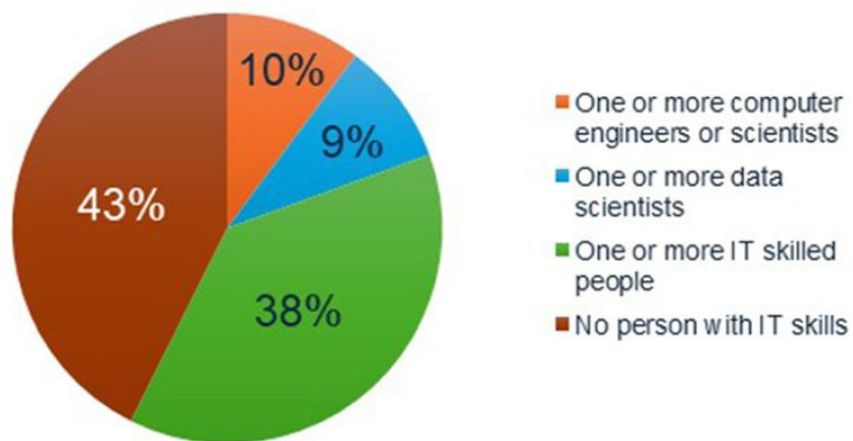


Figure 1: Number of participants per country.

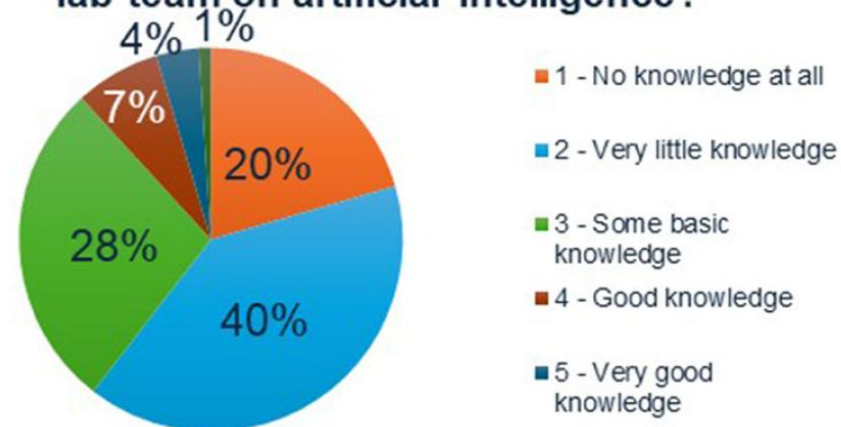
Are there any AI projects going on in your laboratory?



* Does your lab have an employee with A.I. skills?



On a scale of 1-6, on average how would you rate the knowledge of your lab team on artificial intelligence?






Hindernissen voor AI - Opleiding

	n	%
Considering the following items, which one do you believe to hamper the use of AI in lab medicine in the near future? ^a		
Lack of skills and difficulties for understanding too mathematical aspects	125	64.1 %
Issues in data retrieval	78	40.0 %
Untrust in this field of this technological advancement	48	24.6 %
Ethical or regulatory issues	114	58.5 %
Lack of a real improvement patients diagnostic results	57	29.2 %
Lack for equipment	70	35.9 %
None	3	1.5 %
Other	8	4.1 %

	n	%
Would you be interested in a AI training course?		
No	20	10.3 %
Yes	175	89.7 %
How do you think such a course should be organized? ^a		
Basic level (gentle introduction to AI)	109	55.9 %
Intermediate (presentation of specific examples)	125	64.1 %
Advanced (software and coding)	51	26.2 %



	Definition	Prerequisites	Key Question(s) for Medical Education
 <p>Basic skills</p>	Practical ability to use clinical AI tools	Intuitive and user-friendly AI interfaces, and training that involves basic concepts alongside practical experience; Knowledge about specific AI tools used within the clinician’s work environment	What foundational training is needed to be able to use clinical AI tools in medical practice? What are the minimum educational requirements to allow a clinician to operate the AI tools that are in use in their specific clinical setting?
 <p>Proficient skills</p>	Ability to critically assess the utility of clinical AI applications and their outputs as well as the ethical implications of integrating AI in healthcare (in addition to basic skills)	Additional knowledge and scientific skills for interpreting (and conducting) clinical trials and evaluating AI tools according to their value proposition, model performance, potential bias, ethical implications, and healthcare economics	How can clinicians be trained to critically assess AI applications and establish that tools are safe and effective in specific contexts of medical practice? How can clinicians be trained as key stakeholders in ensuring that AI is implemented in healthcare in accordance with ethical and societal values?
 <p>Expert skills</p>	Deep technical understanding of machine learning combined with clinical expertise that enables experts to drive meaningful advancements in medical AI (in addition to proficient skills)	Deep technical understanding of machine learning combined with clinical expertise; Ability to explain clinical challenges to machine learning scientists and understand both potential and limitations of AI for interdisciplinary collaboration OR dual competency for autonomous work	How can clinicians be enabled to proactively foster meaningful innovation in the field of AI in medicine?

We propose three tiers of medical AI expertise alongside definitions, prerequisites, and the key questions for stakeholders in medical education.

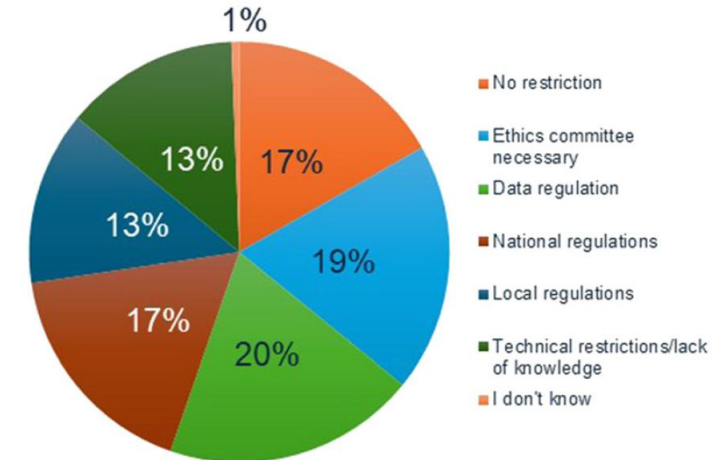
Table 1: Tiers of medical AI expertise.

Hindernissen voor AI - Regelgeving

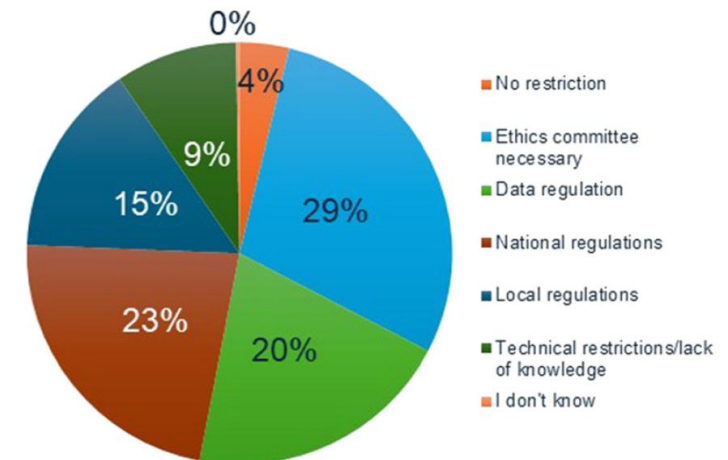
	n	%
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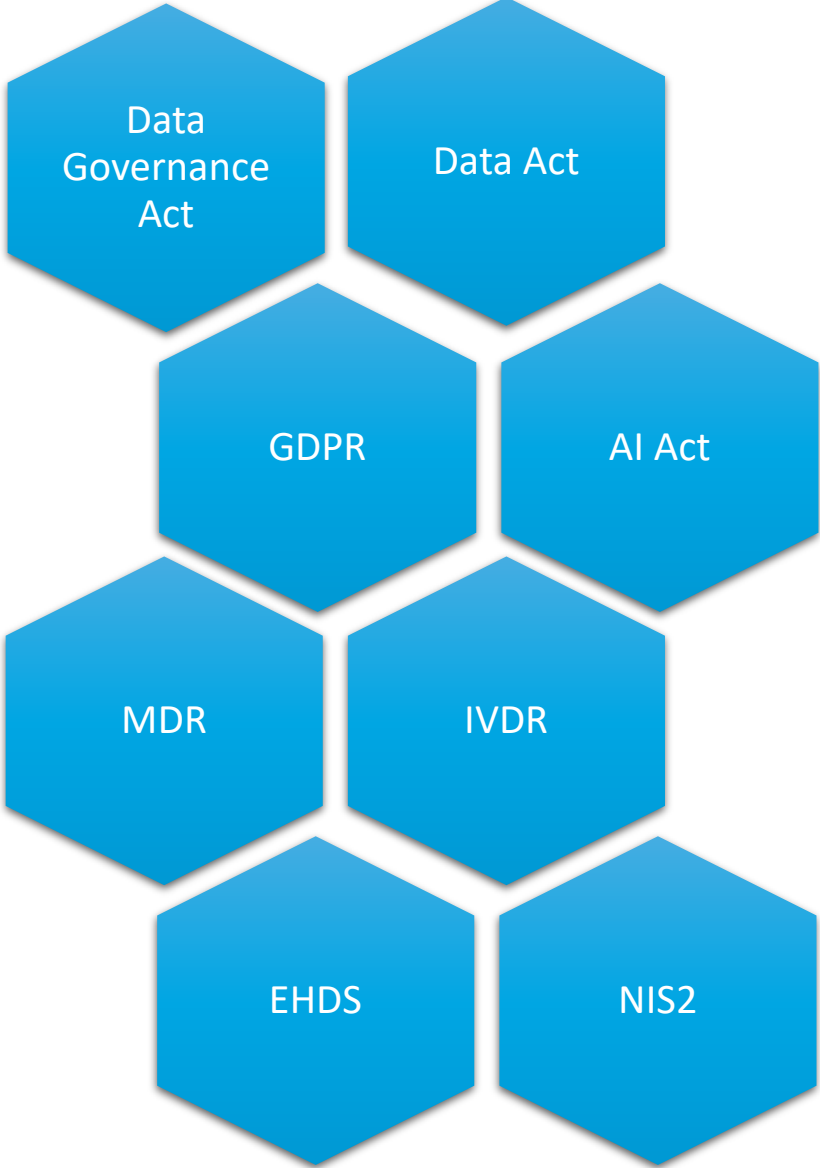
Is there any additional restriction in extracting or using patient data from the Lab-IT (LIS) for...*

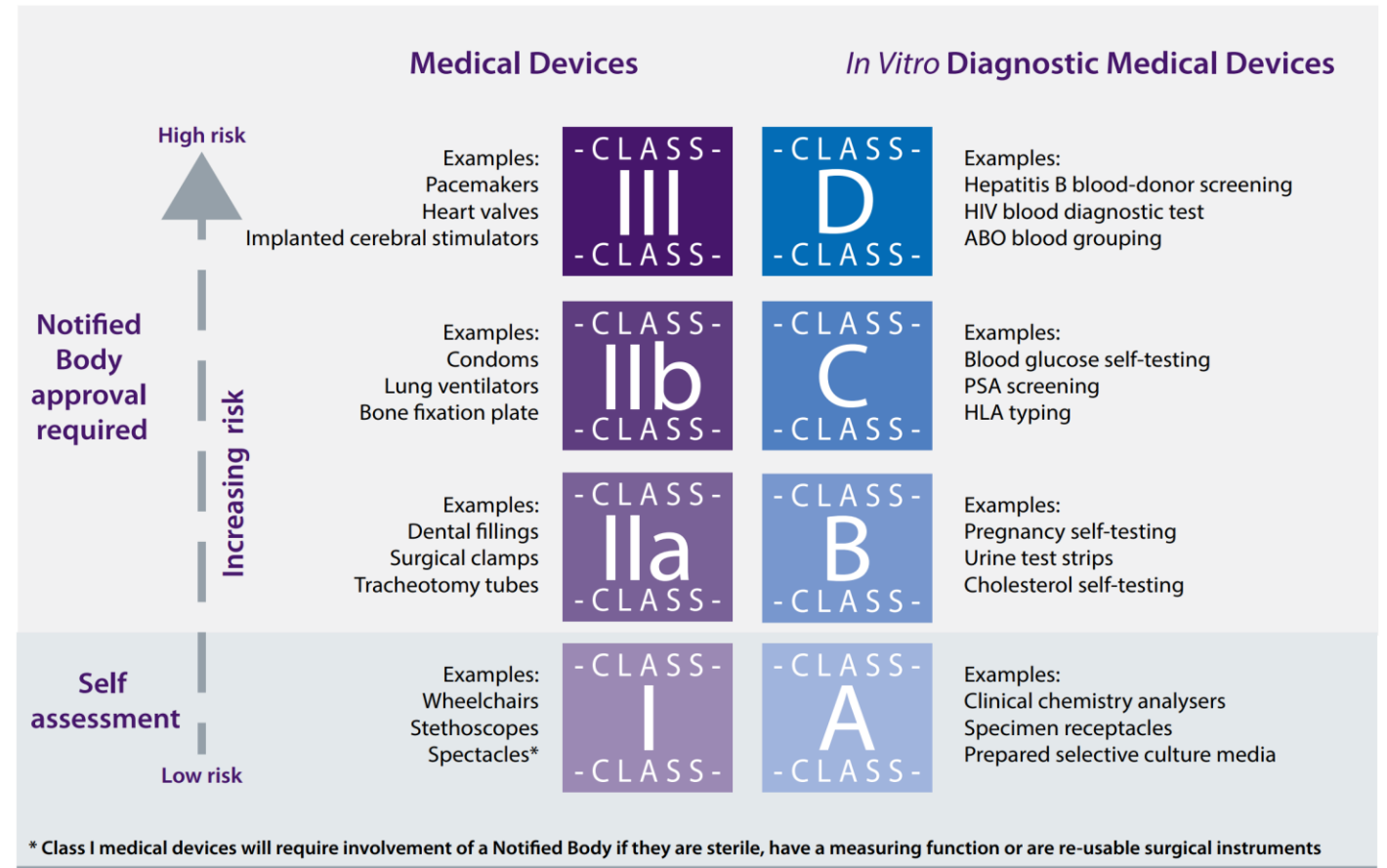
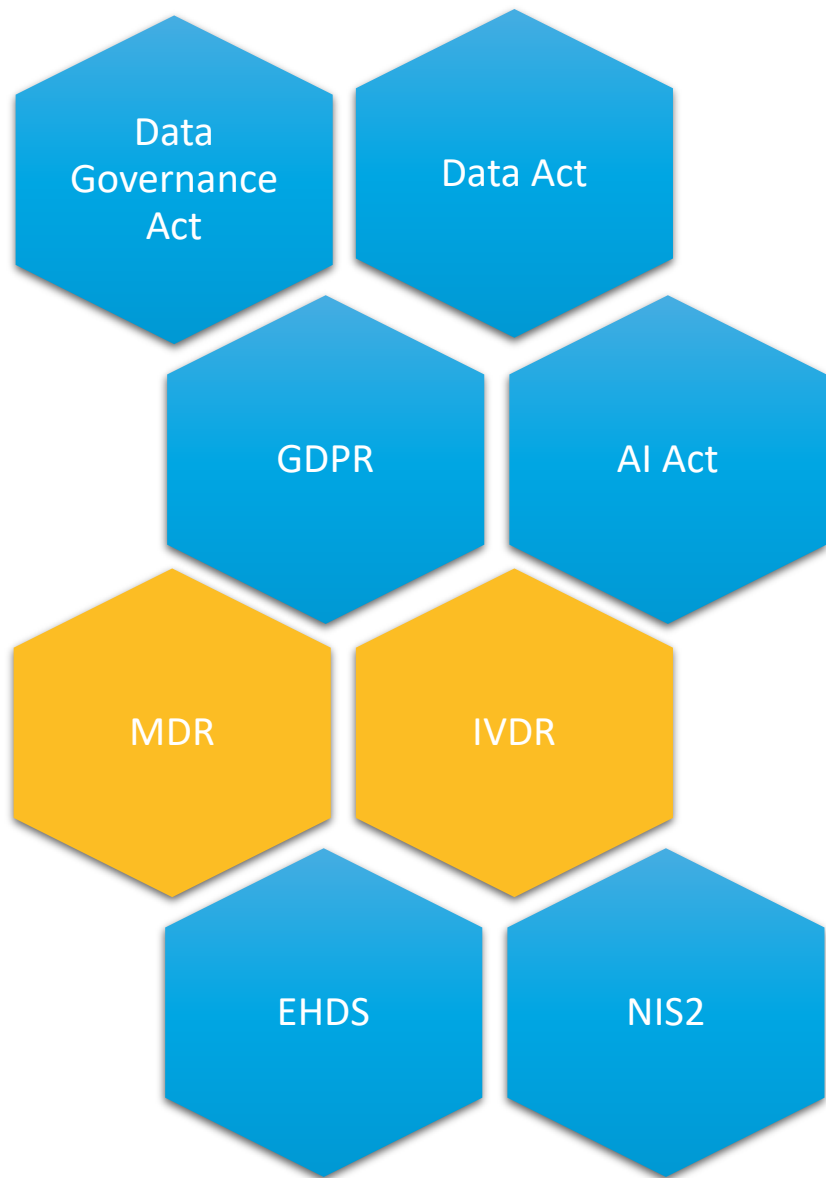
IN-HOUSE USE

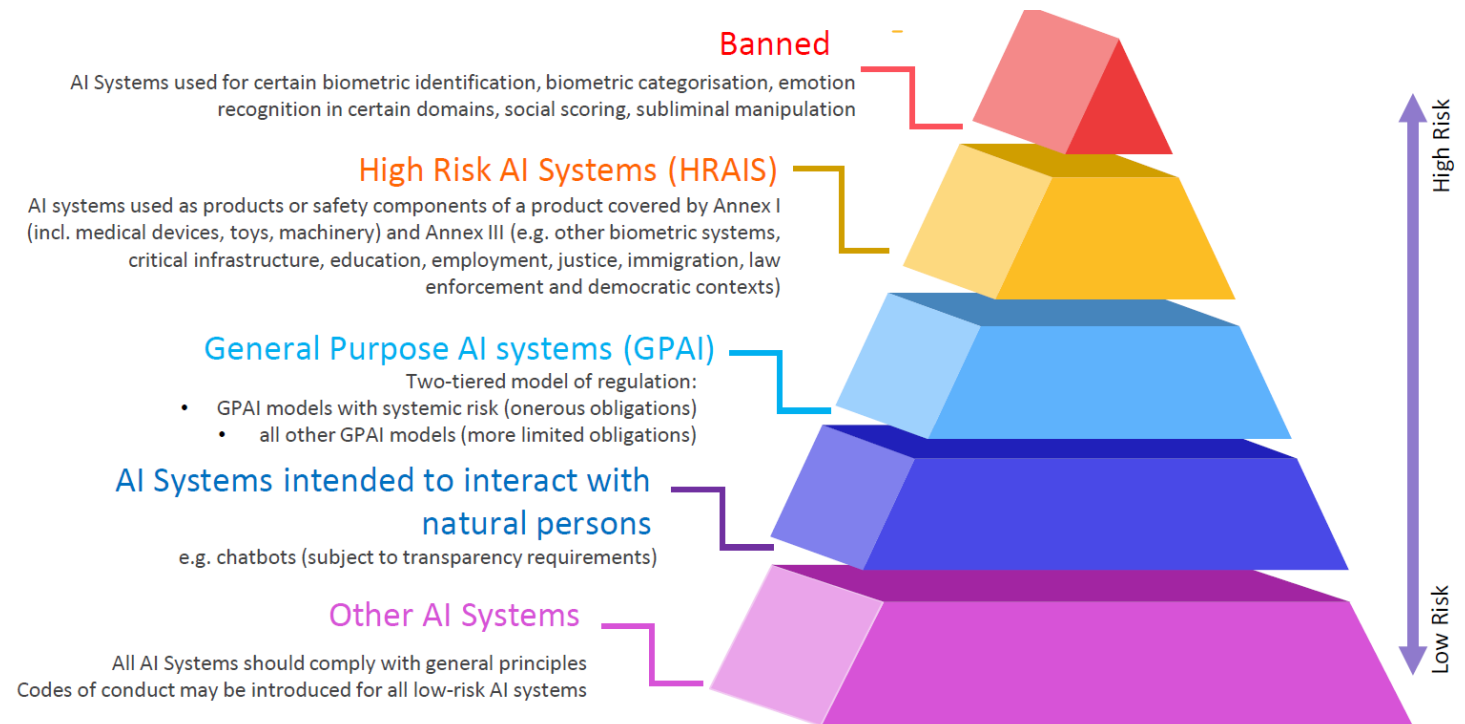
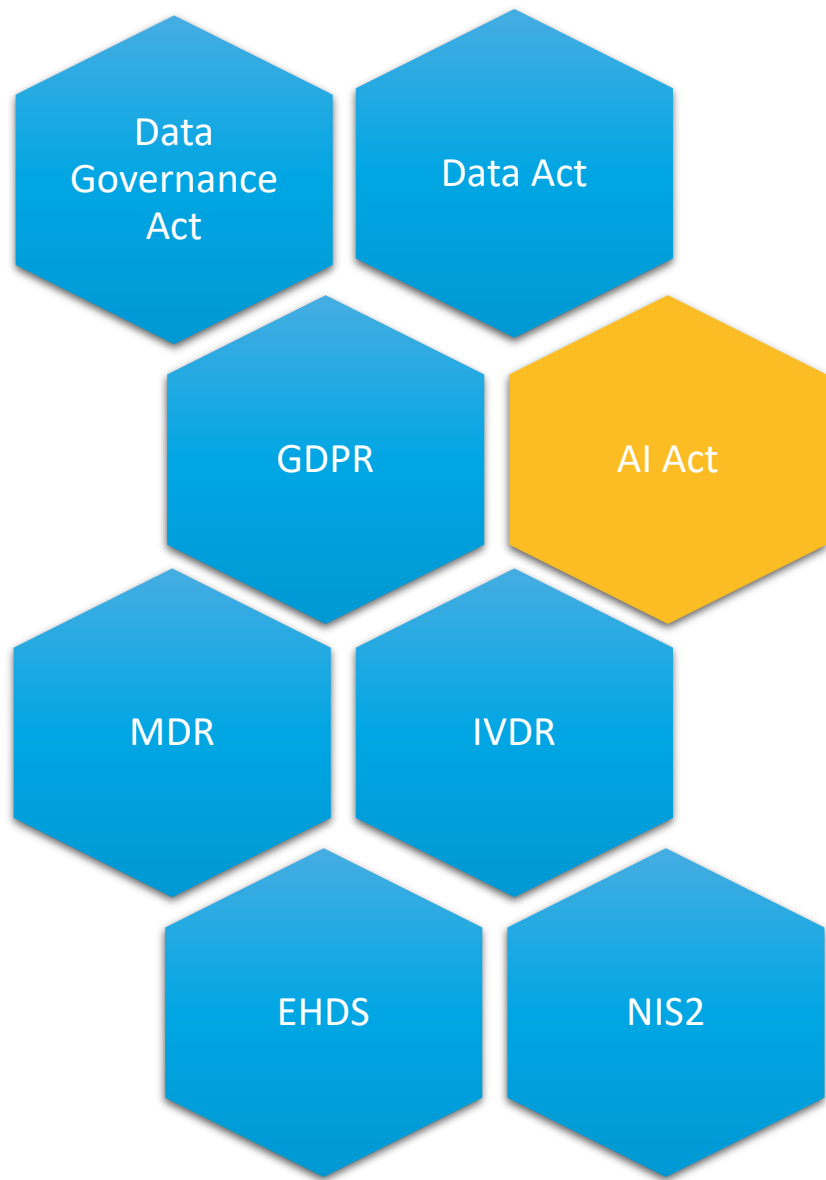


OUTSIDE FACILITY USE





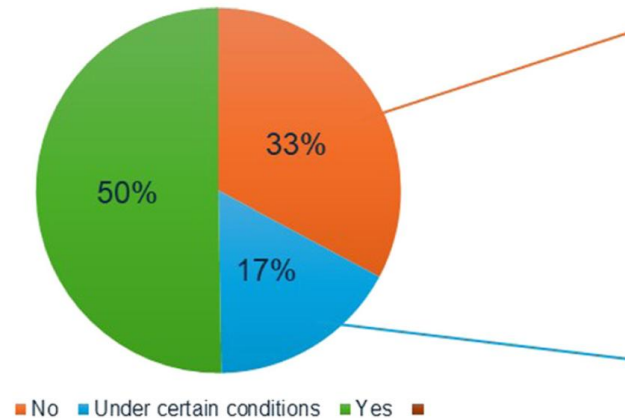




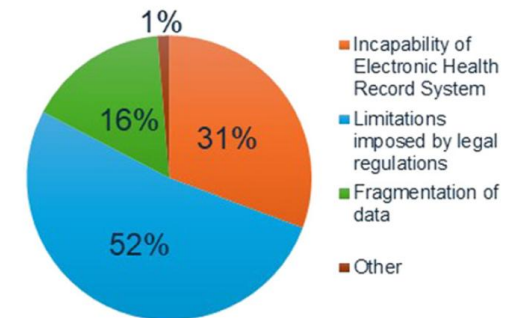
Hindernissen voor AI - Data toegang

	n	%
Considering the following items, which one do you believe to hamper the use of AI in lab medicine in the near future? ^a		
Lack of skills and difficulties for understanding too mathematical aspects	125	64.1 %
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Untrust in this field of this technological advancement	48	24.6 %
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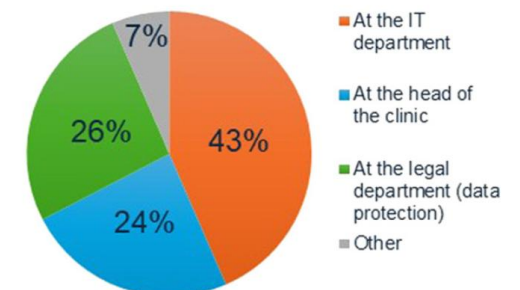
Besides laboratory data, do you have access to other patients' data outside the lab-IT?

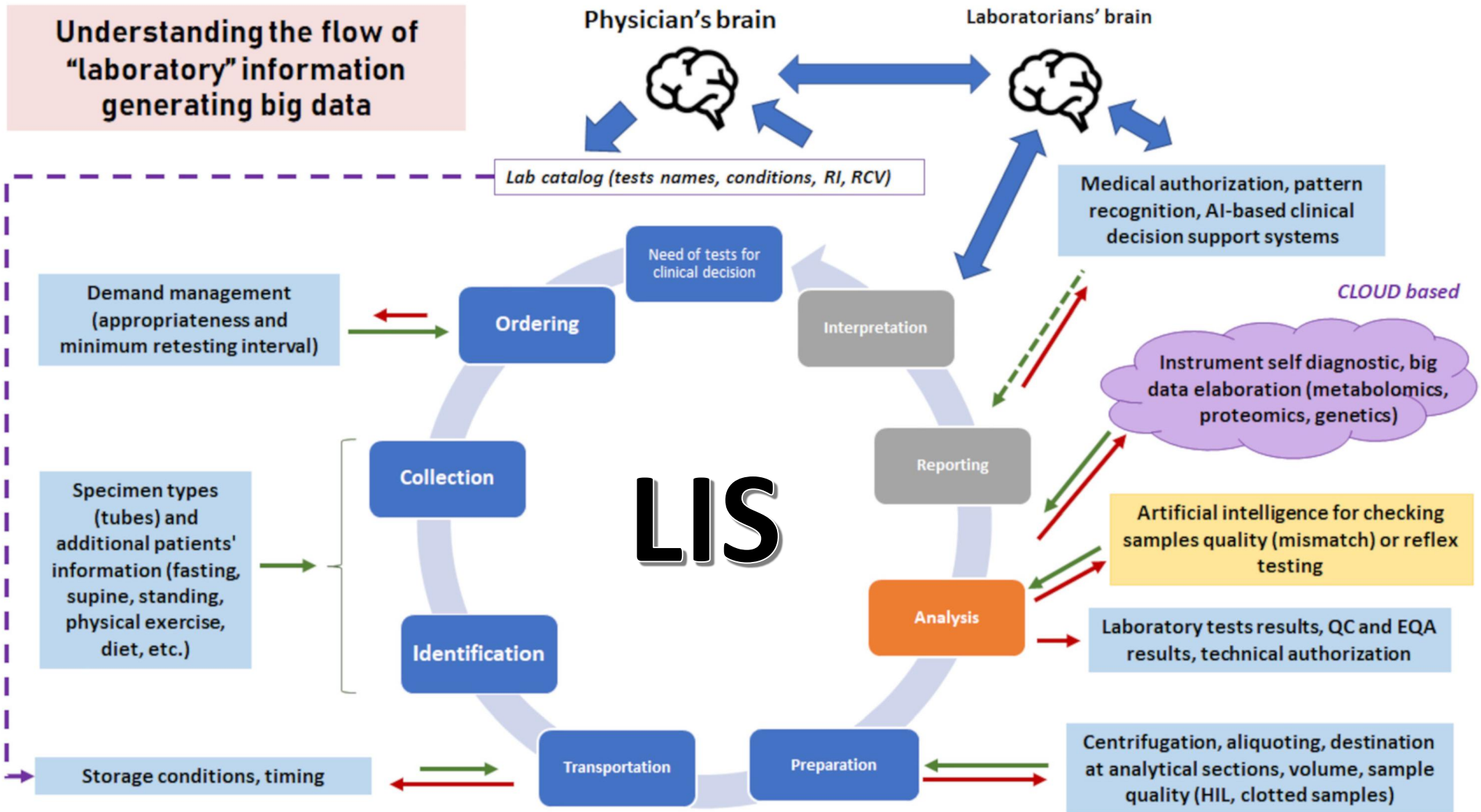


Why can't you access this kind of patient data?

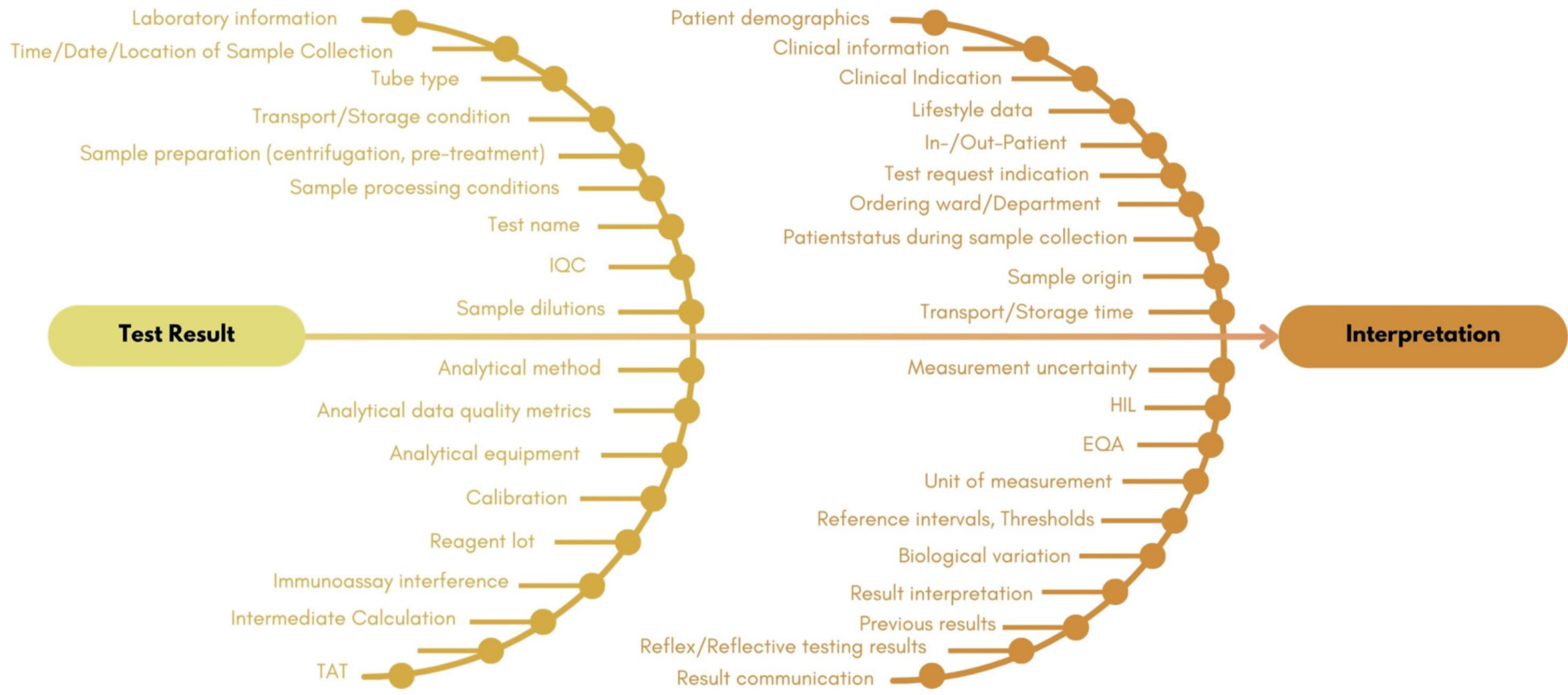


I have to ask for permission...





Primary Data Metadata Peridata



Primary data	Laboratory test results
---------------------	--------------------------------

Metadata	Data derived from the testing process that describe the characteristics and the requirements that are relevant for assessing the quality and the validity of laboratory test results.
Peridata	Data derived from the testing process that are relevant for the interpretation of the results within the clinical context, making that data actionable for the patients' care.

EUDAMED opzoekdatum: 7 februari 2025

- **Medical device software (MDSW), n = 89**

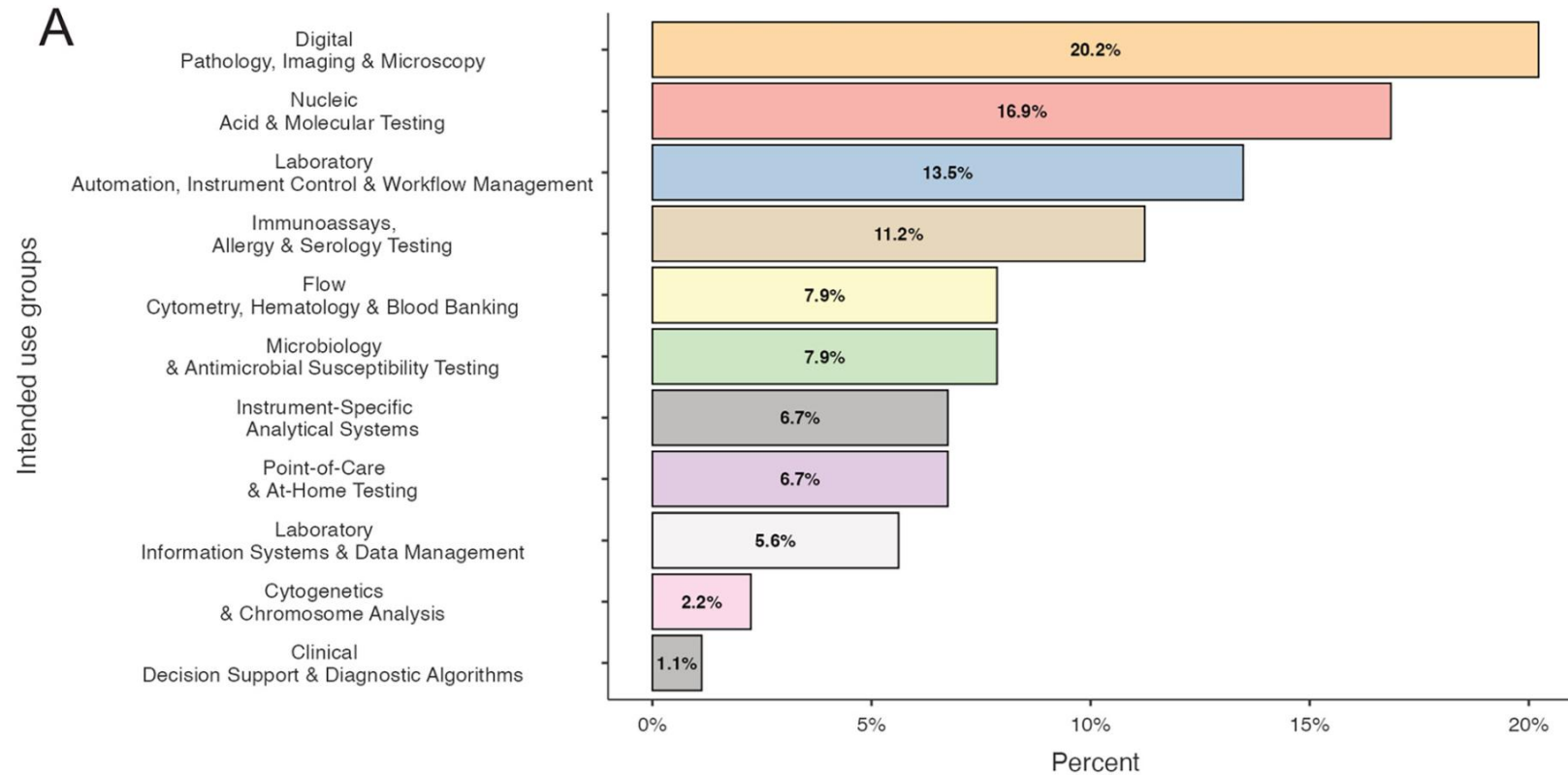


Figure 2: Intended use groups and EU market distribution of medical devices. (A) Distribution of medical devices by intended use group.

EUDAMED opzoekdatum: 7 februari 2025

- **Medical device software (MDSW), n = 89**
- **11/89 = AI software (12,4%):** klasse A (n = 7) en klasse C (n = 4)
 - ✓ Microbiologie
 - ✓ Digitale pathologie
 - ✓ Moleculaire diagnostiek

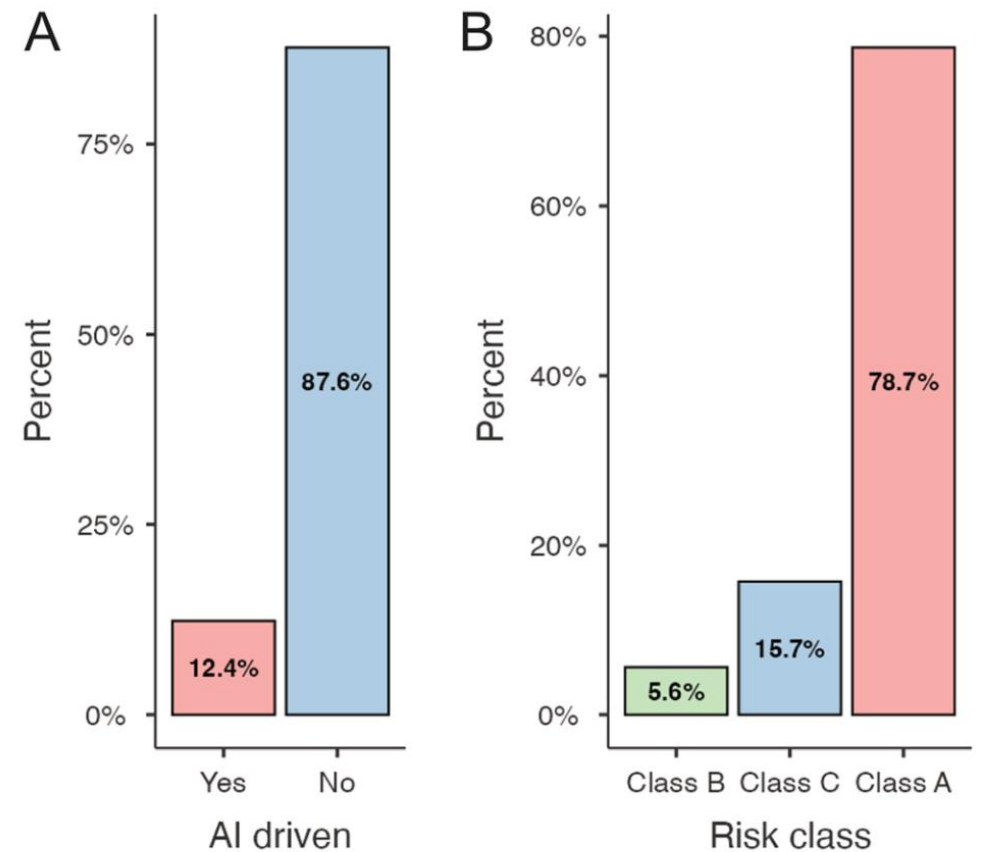


Figure 3: Proportion of AI-driven devices and device risk classifications. (A) Distribution of medical devices based on AI integration. (B) Classification of devices by risk level.

Conclusie

Take home messages

De interesse en toepassingen zijn er, maar we hebben nog nodig:

- Specifieke **opleiding** over (implementatie van) AI in de klinische biologie.
- Kennis over **datatypes**, datatoegang en gegevensdeling.
- Een kader voor implementatie van AI-modellen binnen de **EU-regelgeving**.

Bedankt!

Zijn er vragen?