WashU Medicine

ARTIFICIAL INTELLIGENCE FOR LABORATORY MEDICINE

CSE 4109 Lecture – OCTOBER 1ST, 2026

Mark A. Zaydman, MD, PhD
Associate Professor of Pathology and Immunology
Washington University School of Medicine
Saint Louis, Missouri, United States of America

Disclosures

Mark A. Zaydman, MD, PhD

- Advisory Board/Committee: Diasorin
- Research Support: BioMerieux, Sebia
- Honorarium: Roche, Siemens, Sebia

Non of these activities directly pertain to the contents of this presentation

What Is Laboratory Medicine?

- A branch of healthcare focused on analyzing (testing) clinical biospecimens
  - Blood
  - Urine
  - Cerebrospinal fluid
- Core areas
  - Clinical chemistry
  - Hematology
  - Microbiology
  - Molecular
  - Toxicology



Laboratory Testing Helps Address Medical Uncertainty

- Diagnosis
- Prognosis
- Treatment



WERTMAN BG JAMA 1980:243:2080-2

Laboratory Testing Is The GPS For Healthcare

When testing is working well



When laboratory testing is working well, it helps the patients and doctors navigate critical decisions to steer the patient toward the best health

‘Bad’ Laboratory Testing Leads To ‘Bad’ Outcomes

When testing is working well



When testing is **NOT** working well



Testing Errors Lead To Patient Harm

Missed diagnosis

Preventable morbidity

Preventable mortality

Misdiagnosis

Unnecessary follow up and treatment

Delay of correct diagnosis

Anxiety

Financial toxicity

Direct impact on personal finances

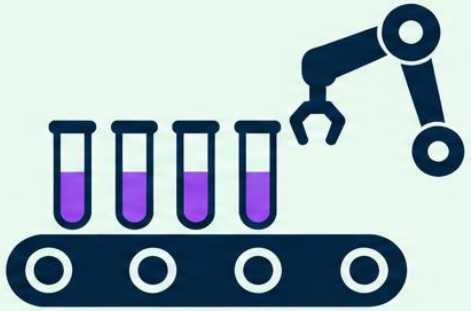
May lead to healthcare avoidance

can AI improve laboratory medicine?

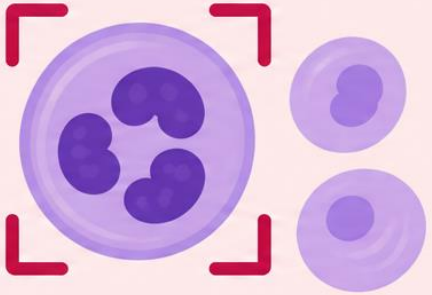
AI Already Exists In The Clinical Laboratory



Verification logic



Automation lines



Cell classification tools

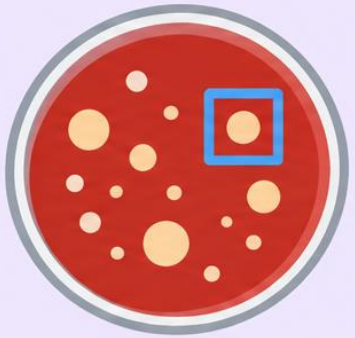
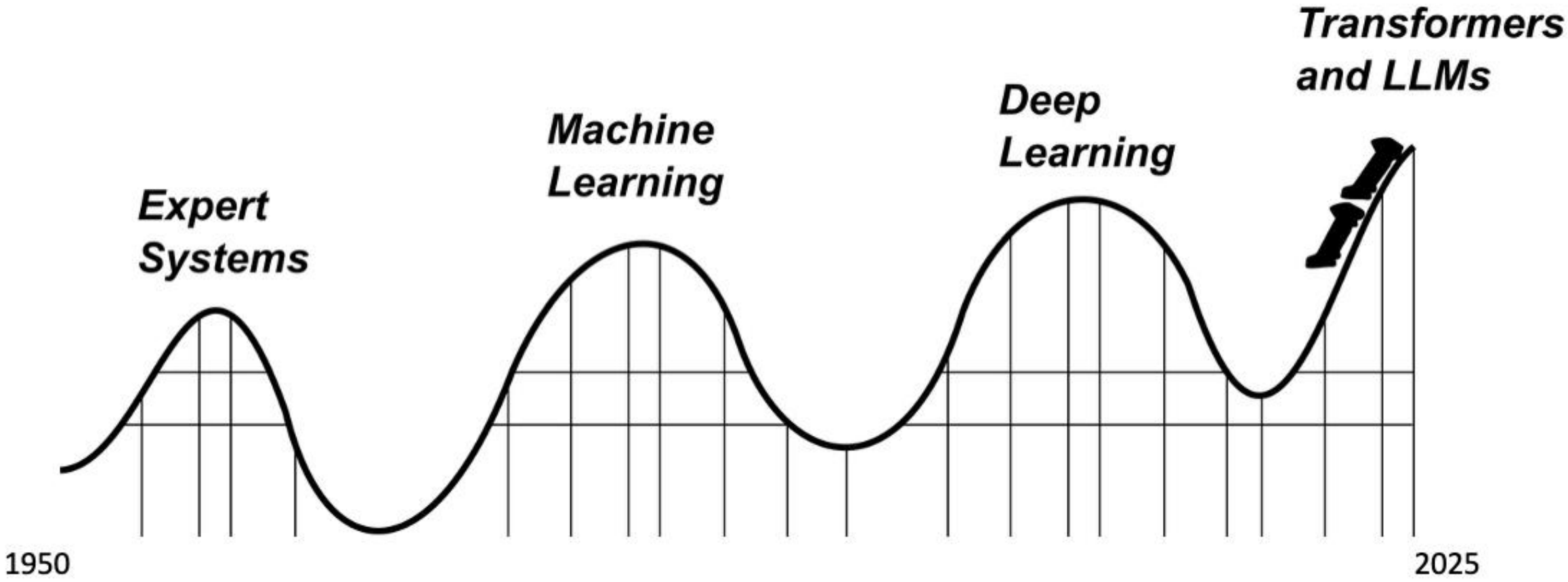


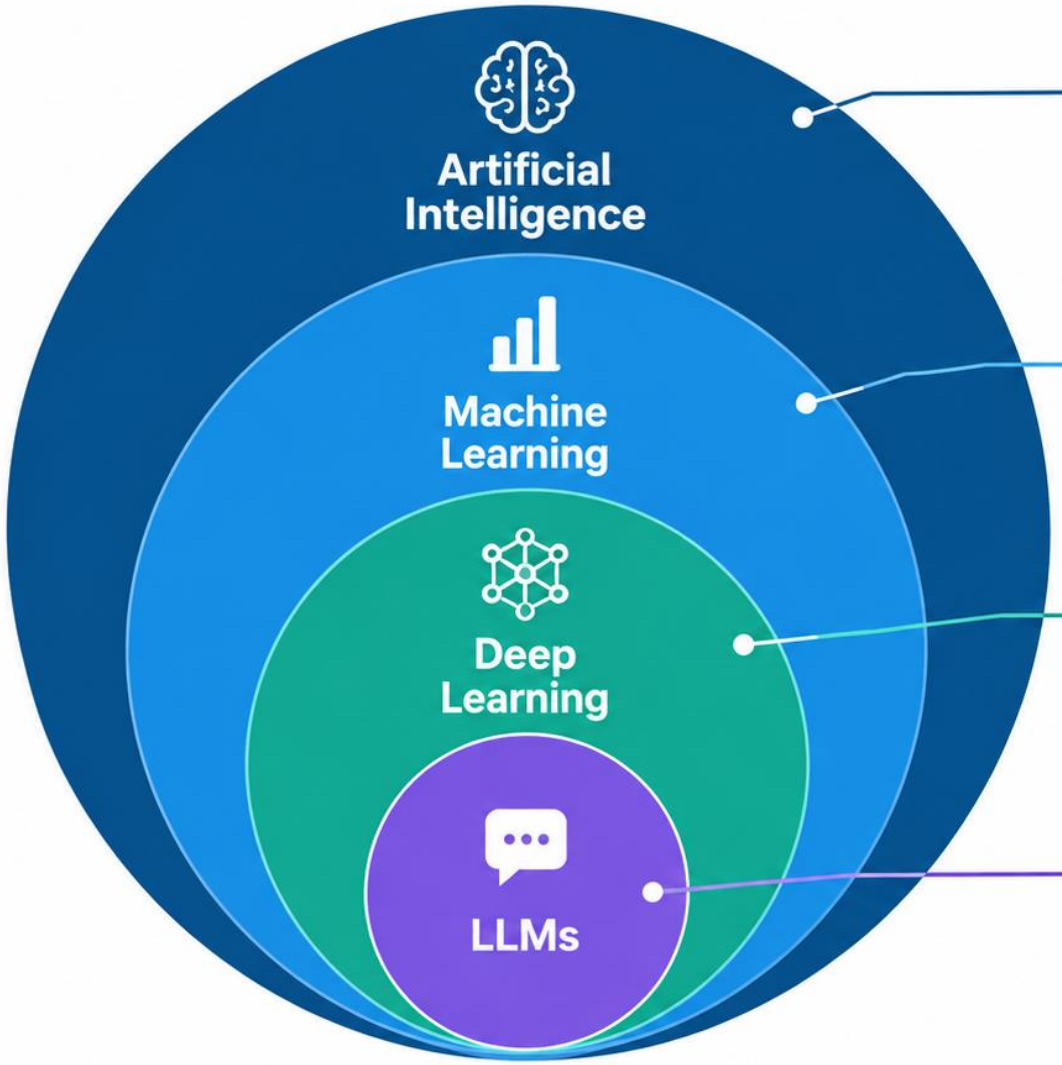
Image-based microbiology analysis

IMAGE GENERATED WITH CHATGPT

AI Is Not New, But The Technology Is Ever Evolving



A Broad Definition Of AI



Artificial Intelligence
Broadly defined as machines that perform tasks that typically require human intelligence (e.g., reasoning, perception, decision-making)

Machine Learning
Algorithms that learn patterns from data without being explicitly programmed

Deep Learning
Machine learning using neural networks to learn complex patterns in unstructured data (e.g., images, text, audio)

Large Language Models
A type of deep learning model trained on large amounts of text to understand and generate human language

IMAGE GENERATED WITH CHATGPT

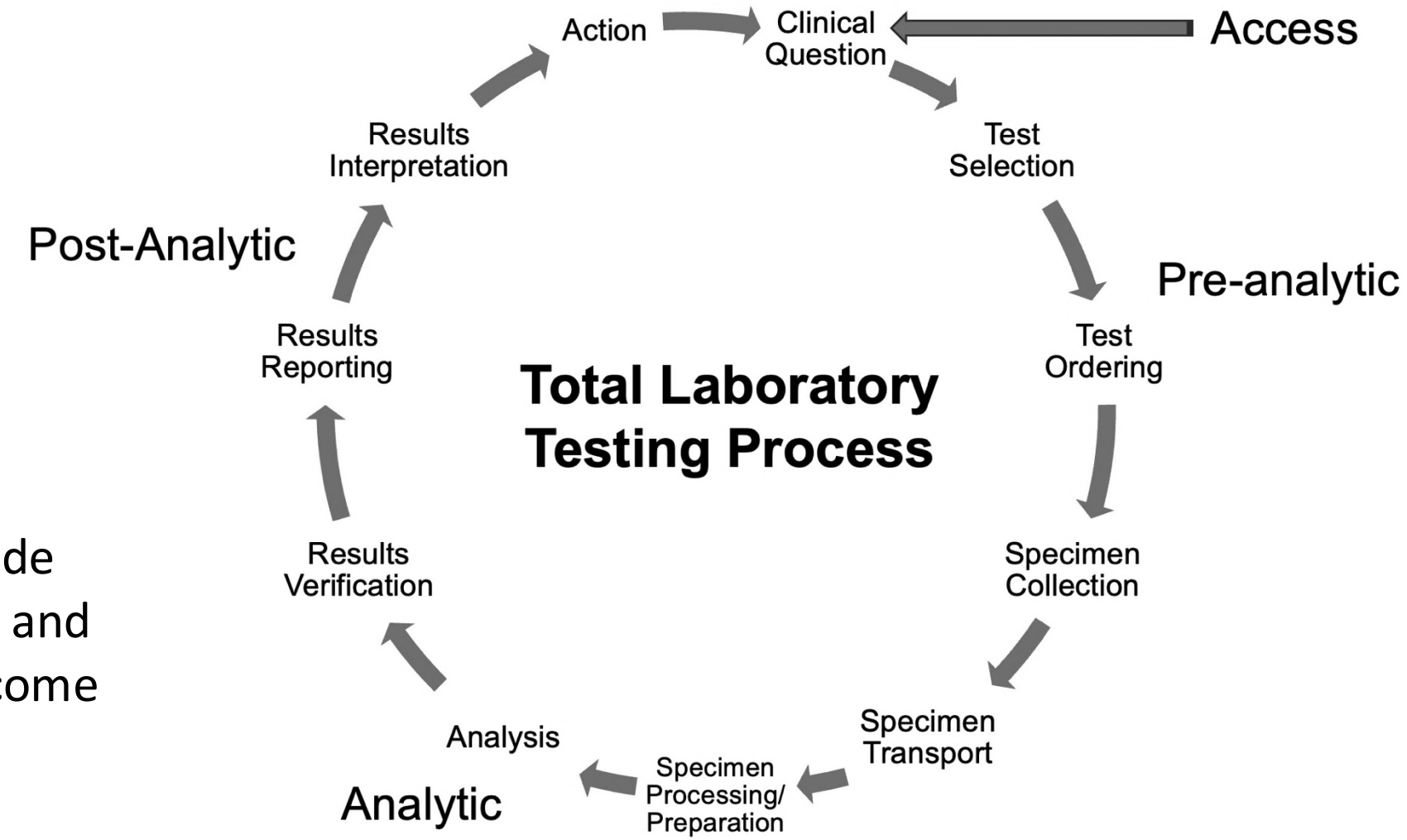
more

Where can ^ AI

improve

laboratory medicine?

Ensuring Laboratory Quality Is Complex



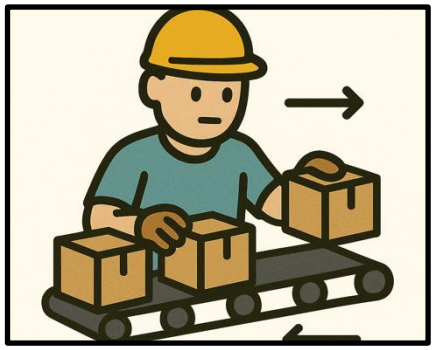
Any break in this process can degrade laboratory quality and lead to a bad outcome for the patient

Slide courtesy of Vahid Azimi | Adapted from: Raab, Swain, Smith, and Grzybicki. Clin Biochem. 2013 Sep;46(13-14):1180-6.

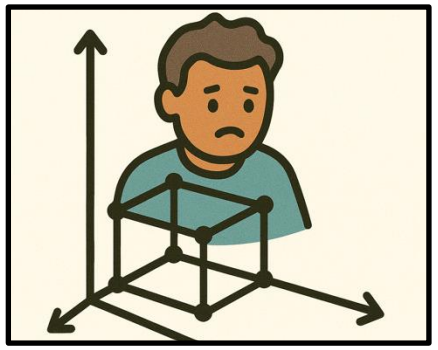
Many Manual Laboratory Tasks Are High Value AI Targets



Dangerous



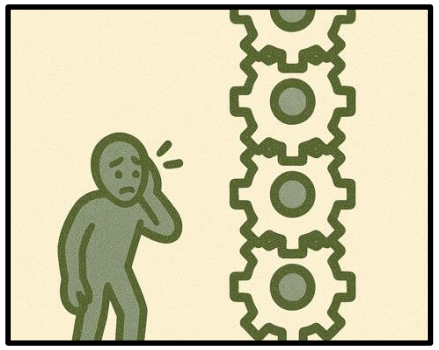
Repetitive



Complex



High precision

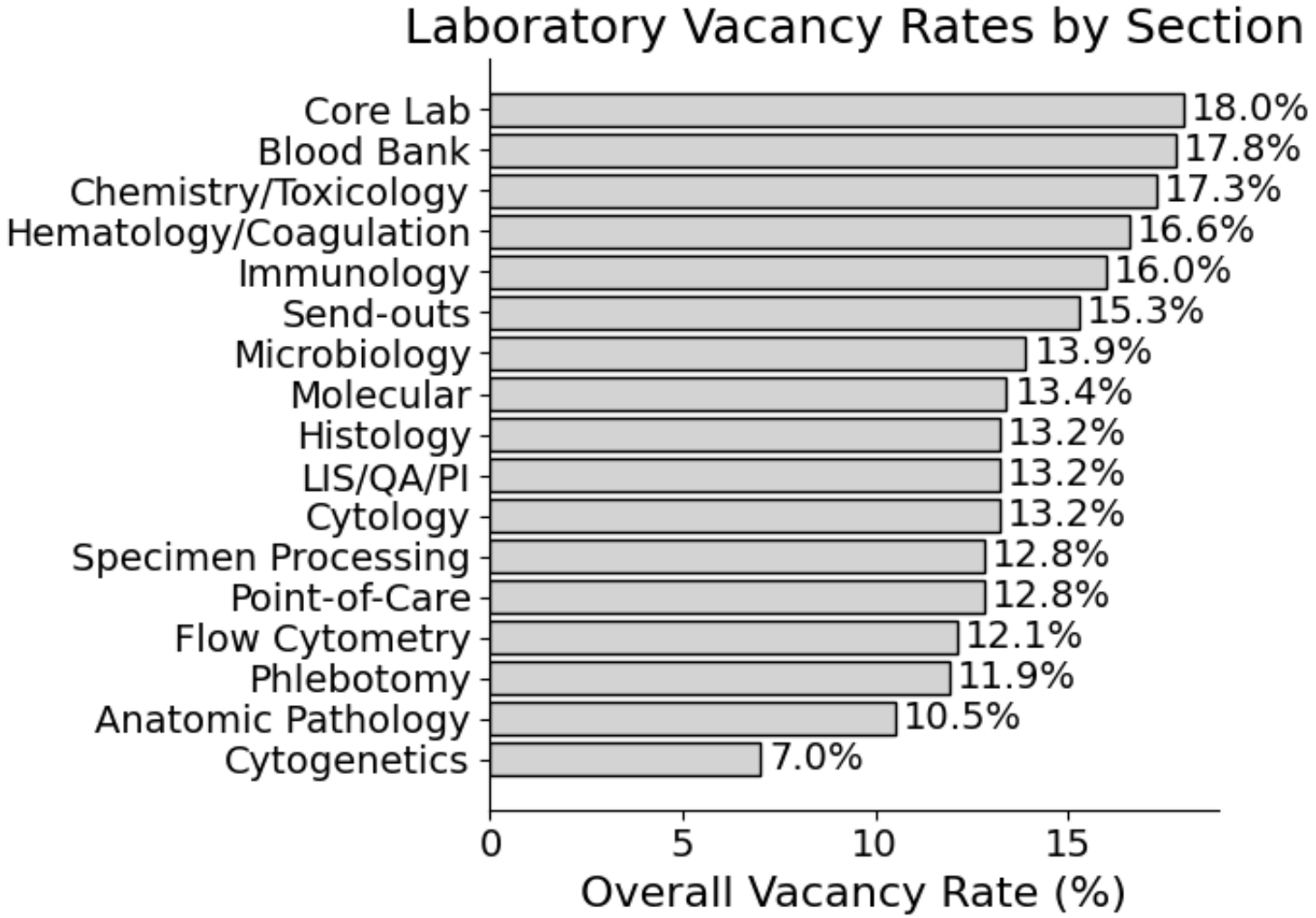


Scale

Such tasks are found throughout laboratory testing

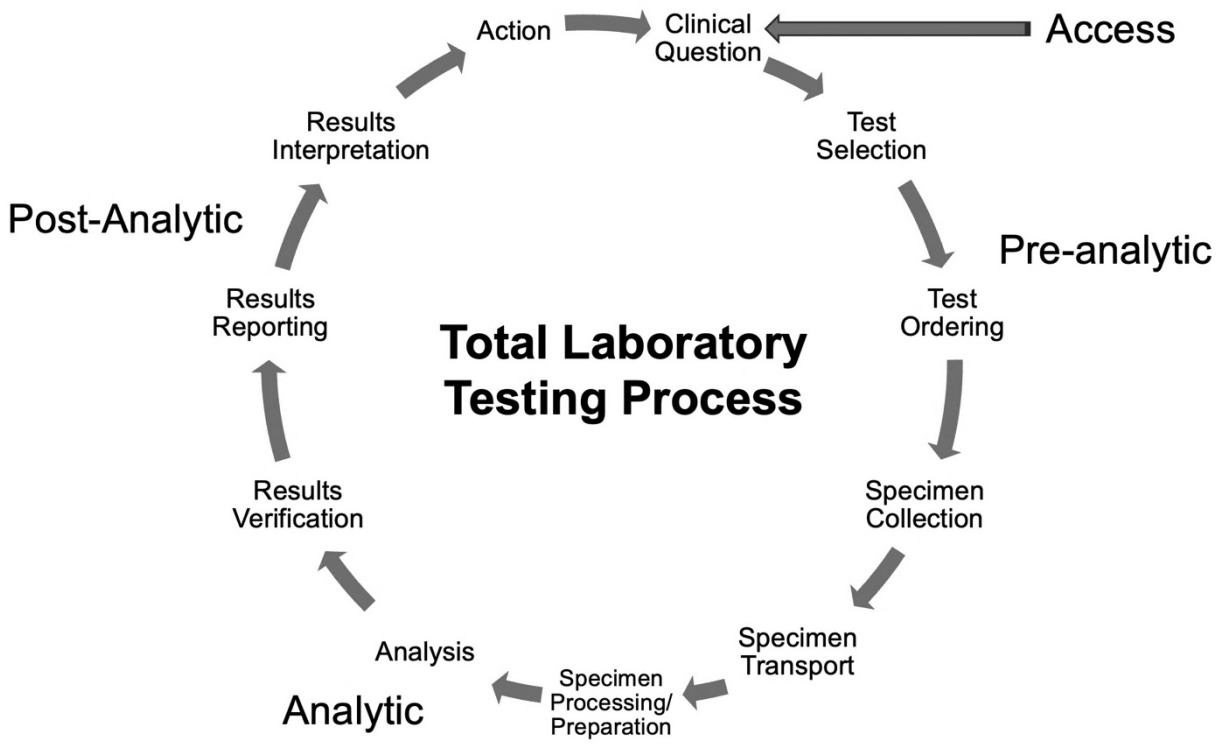
IMAGES GENERATED WITH CHATGPT

Laboratories Are Facing Historic Staffing Shortages

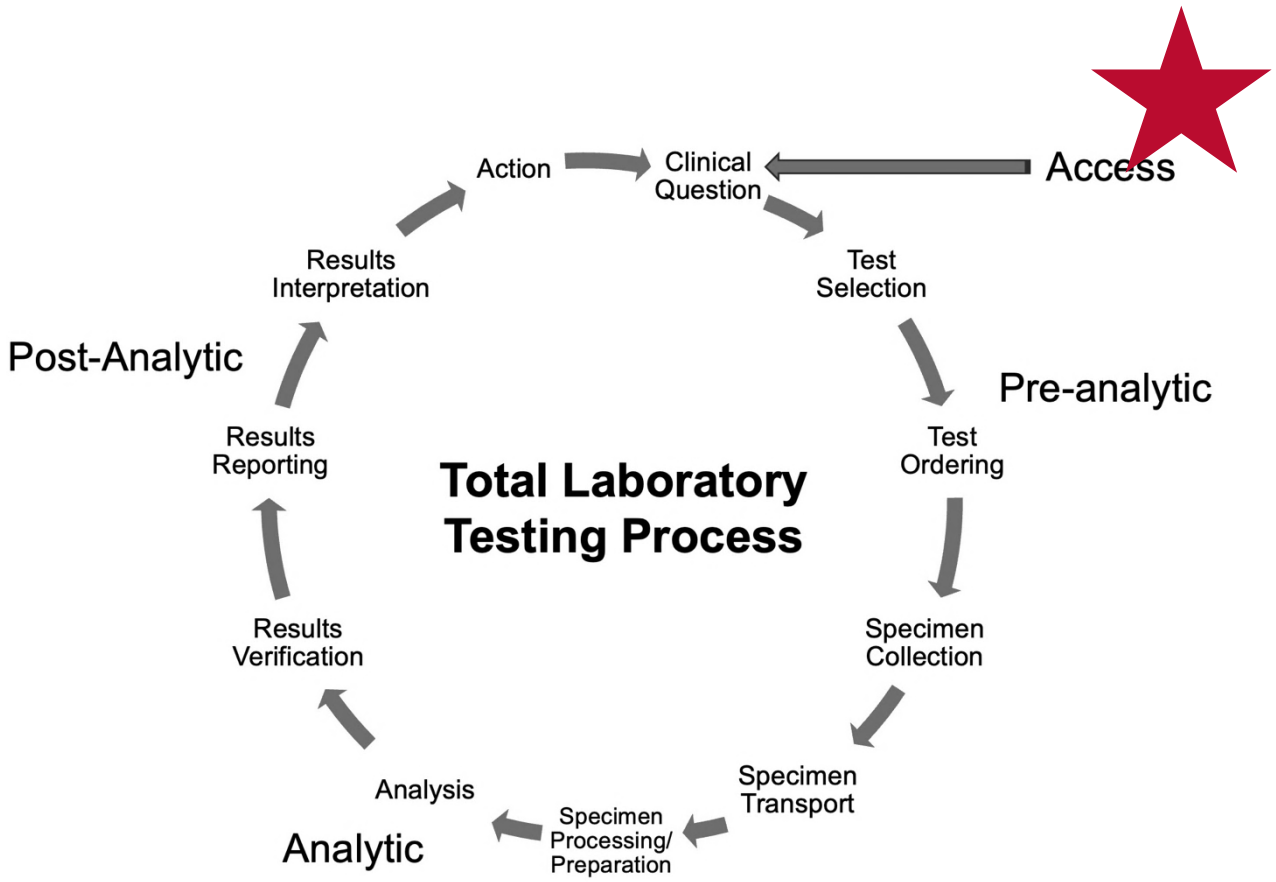


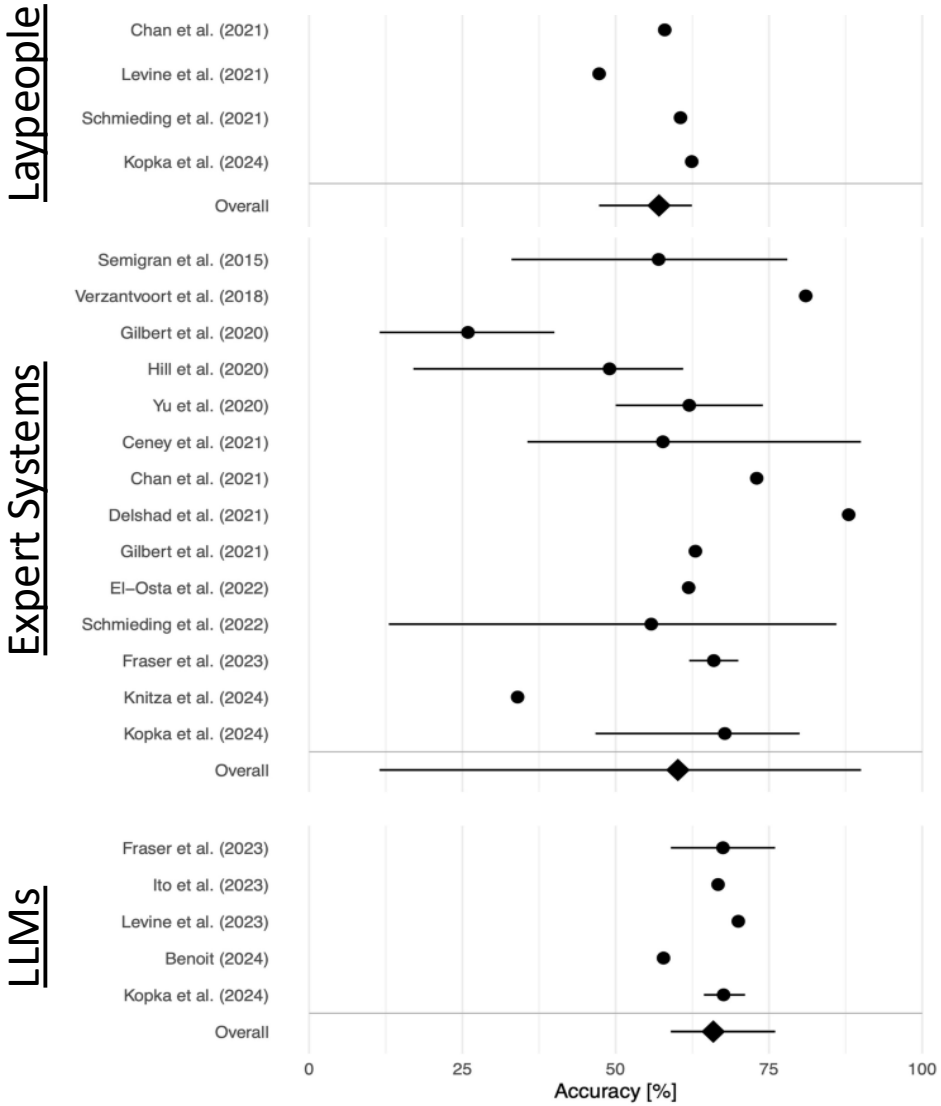
GARCIA 2024 AM J CLIN PATHOL PMID: 37936416

AI Opportunities Throughout The Testing Process



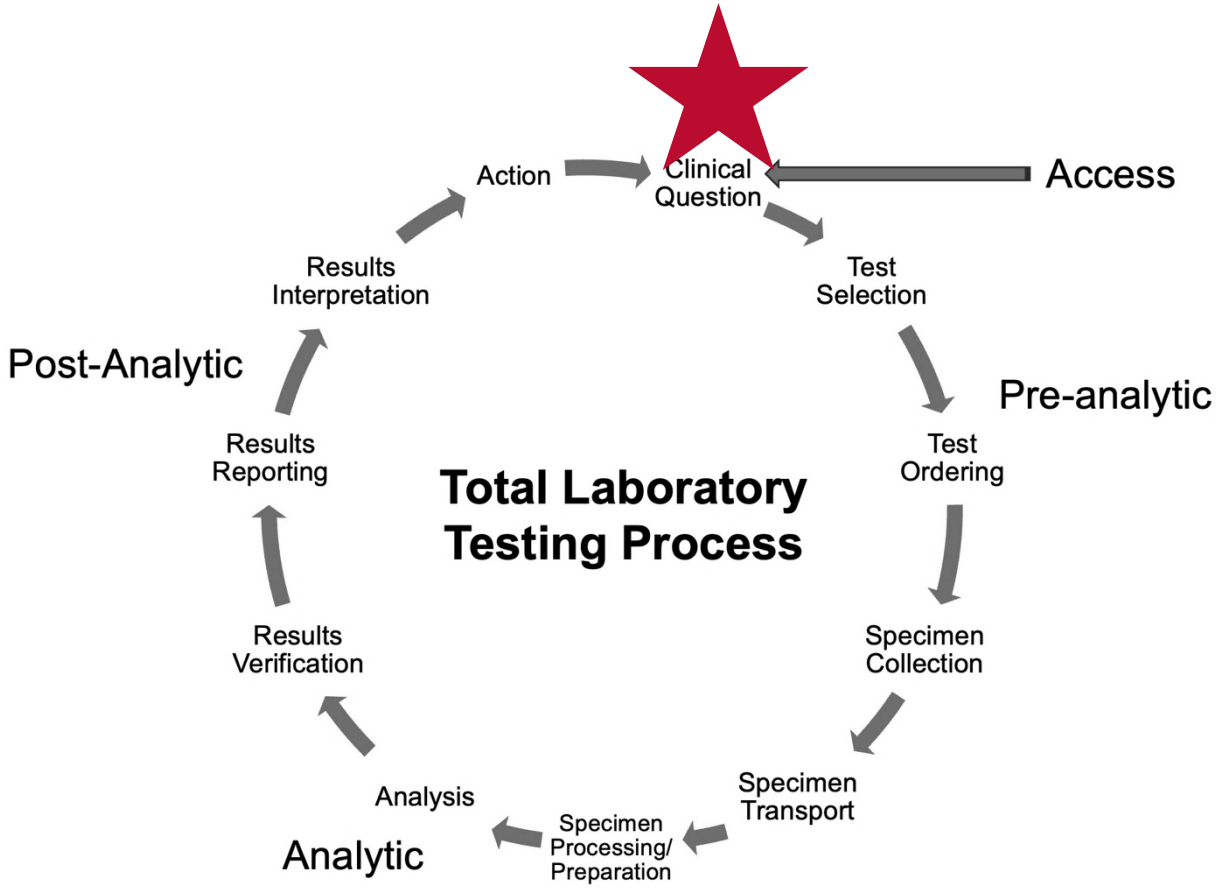
AI Opportunities Throughout The Testing Process

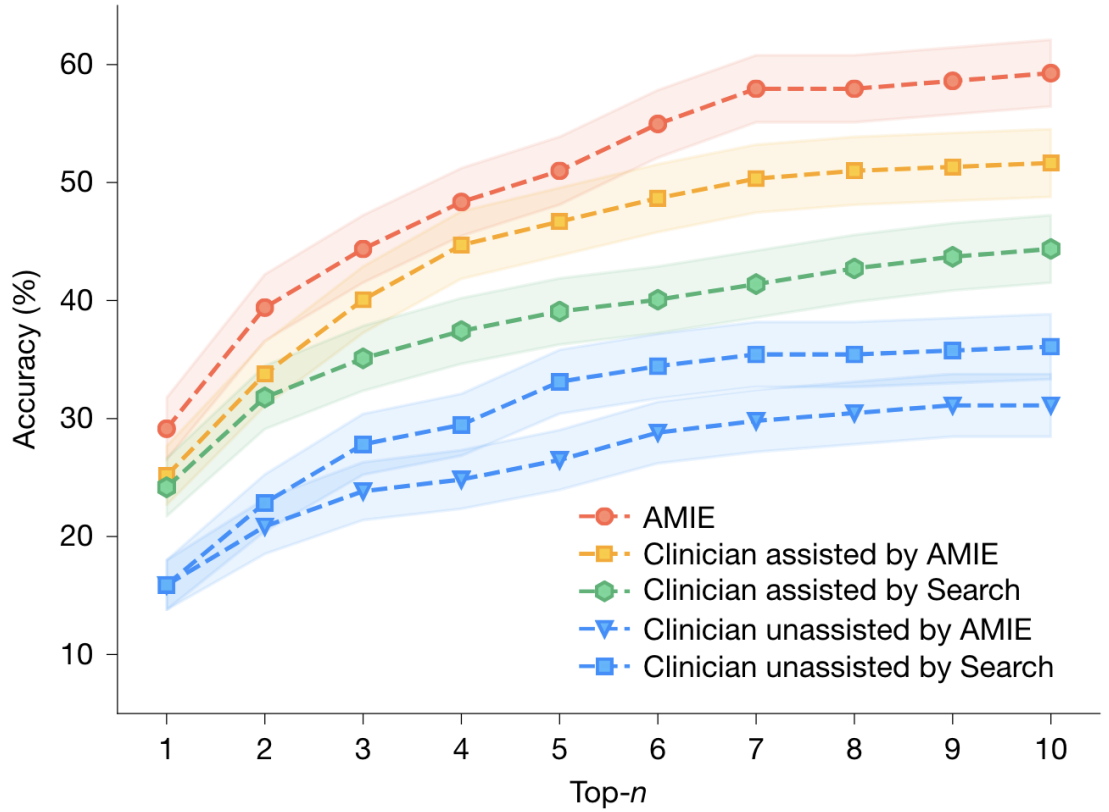




KOPKA, M. *NPJ DIGIT. MED.* 2025, *8* (1), 178. PMID: 40133390

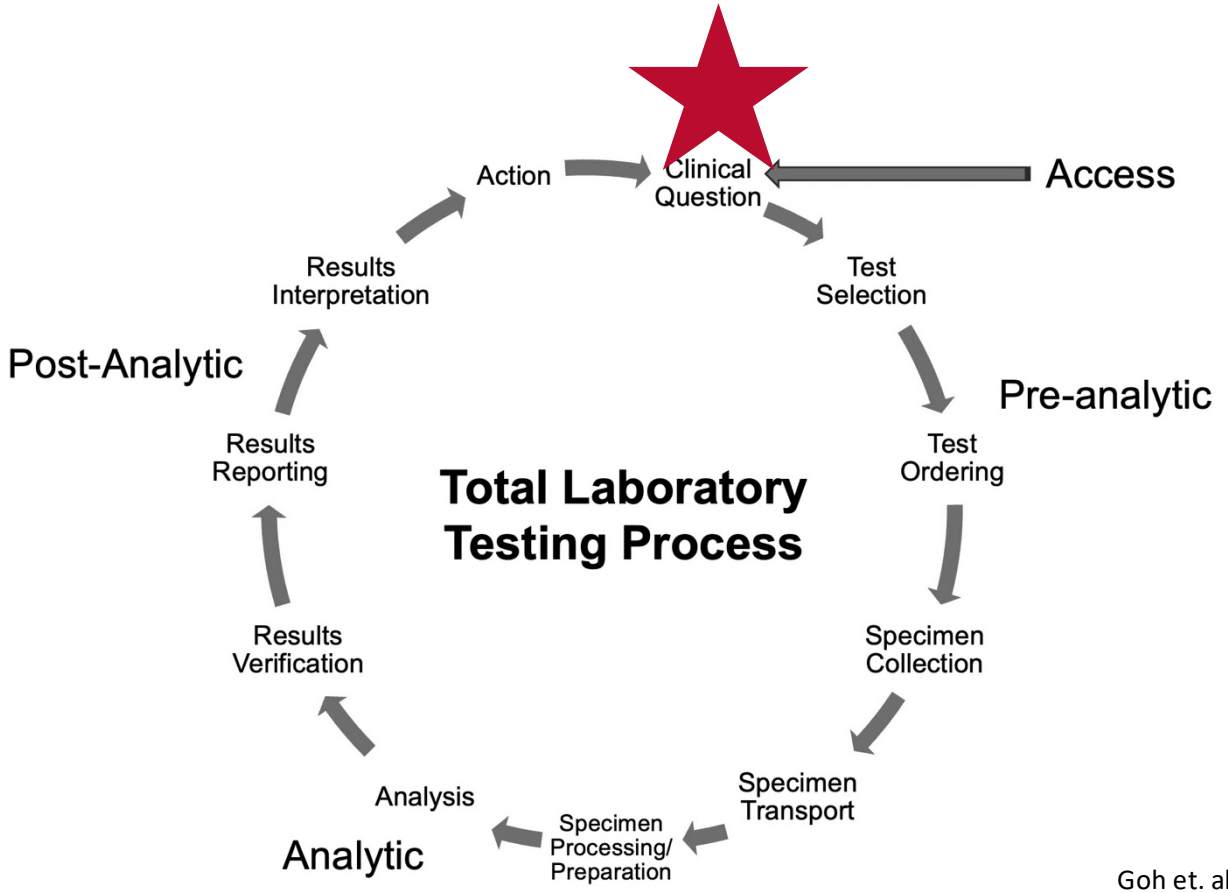
AI Opportunities Throughout The Testing Process

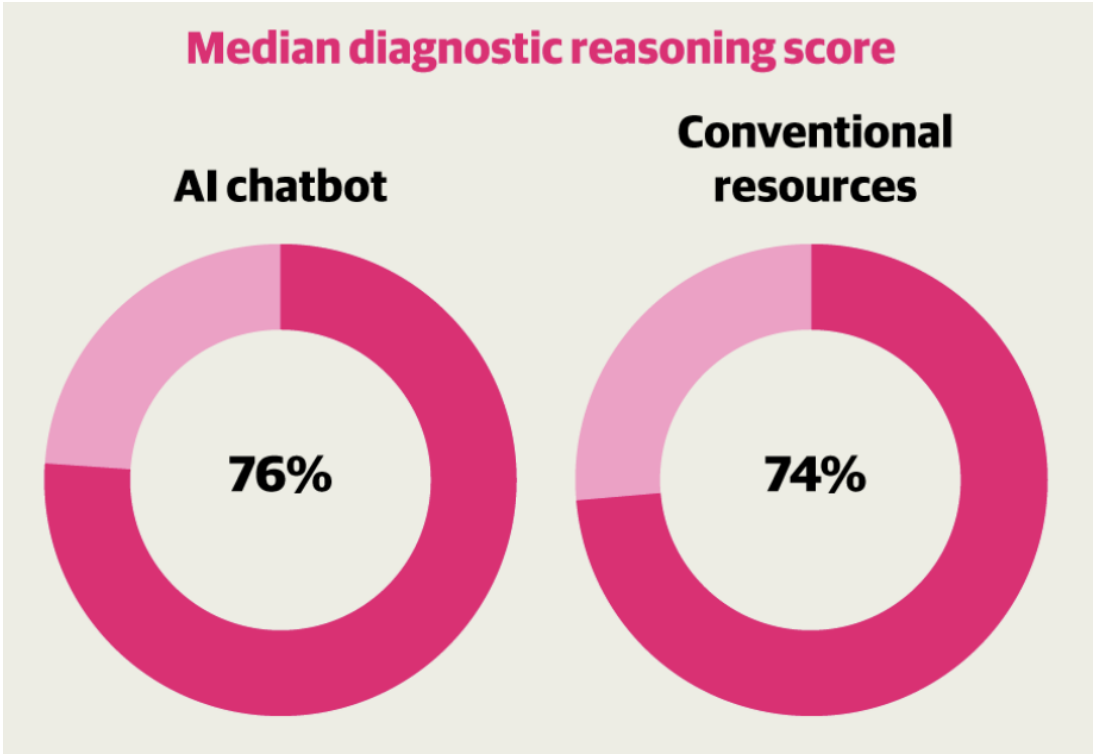




McDuff et al. *Nature* 642, no. 8067 (June 12, 2025): 451–57. https://doi.org/10.1038/s41586-025-08869-4.

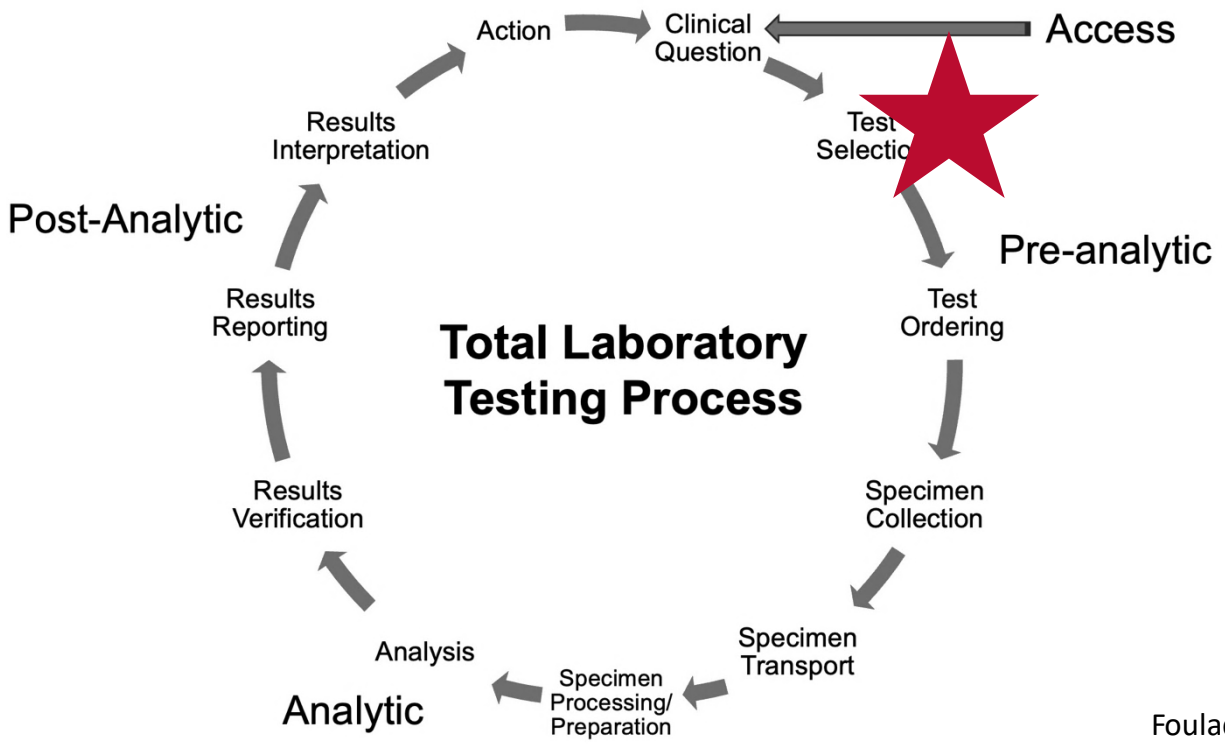
AI Opportunities Throughout The Testing Process



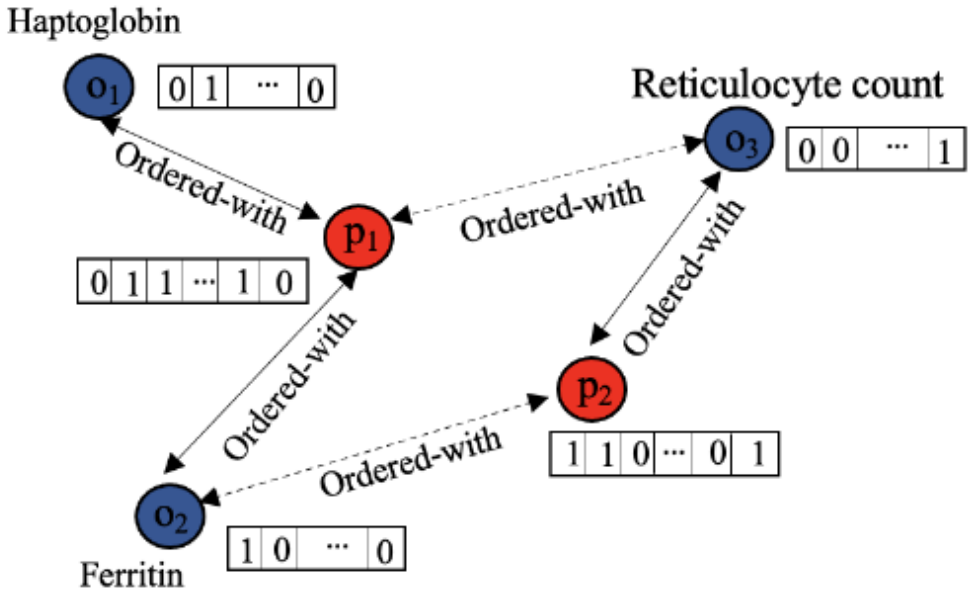


Goh et. al. *JAMA Netw Open* **2024**, *7* (10), e2440969. https://doi.org/10.1001/jamanetworkopen.2024.40969.

AI Opportunities Throughout The Testing Process

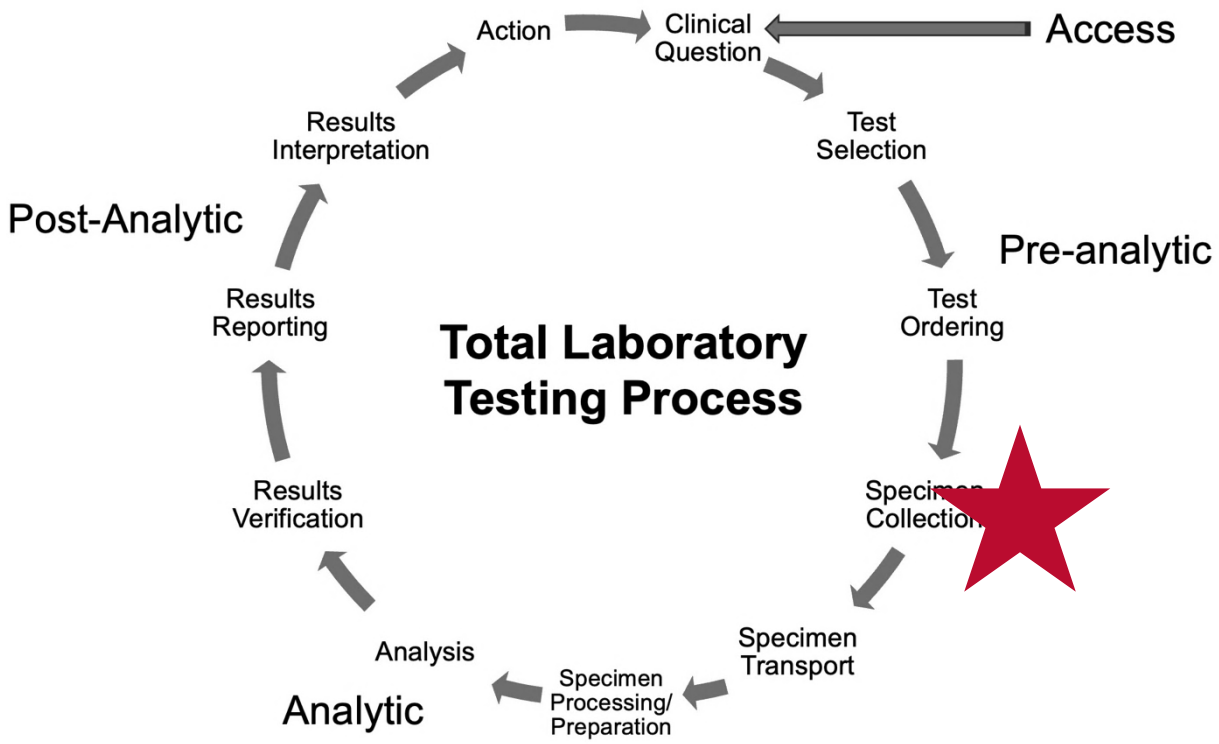


Order Recommender Systems

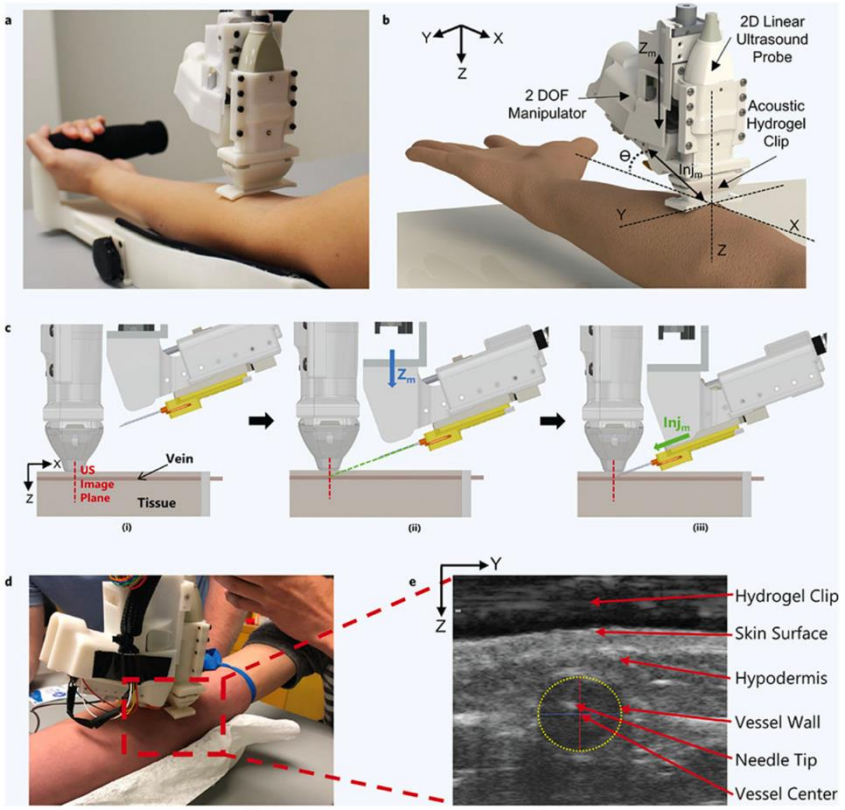


Fouladvand S, et. al.. J Biomed Inform. 2023 Jul;143:104407. doi: 10.1016/j.jbi.2023.104407.

AI Opportunities Throughout The Testing Process

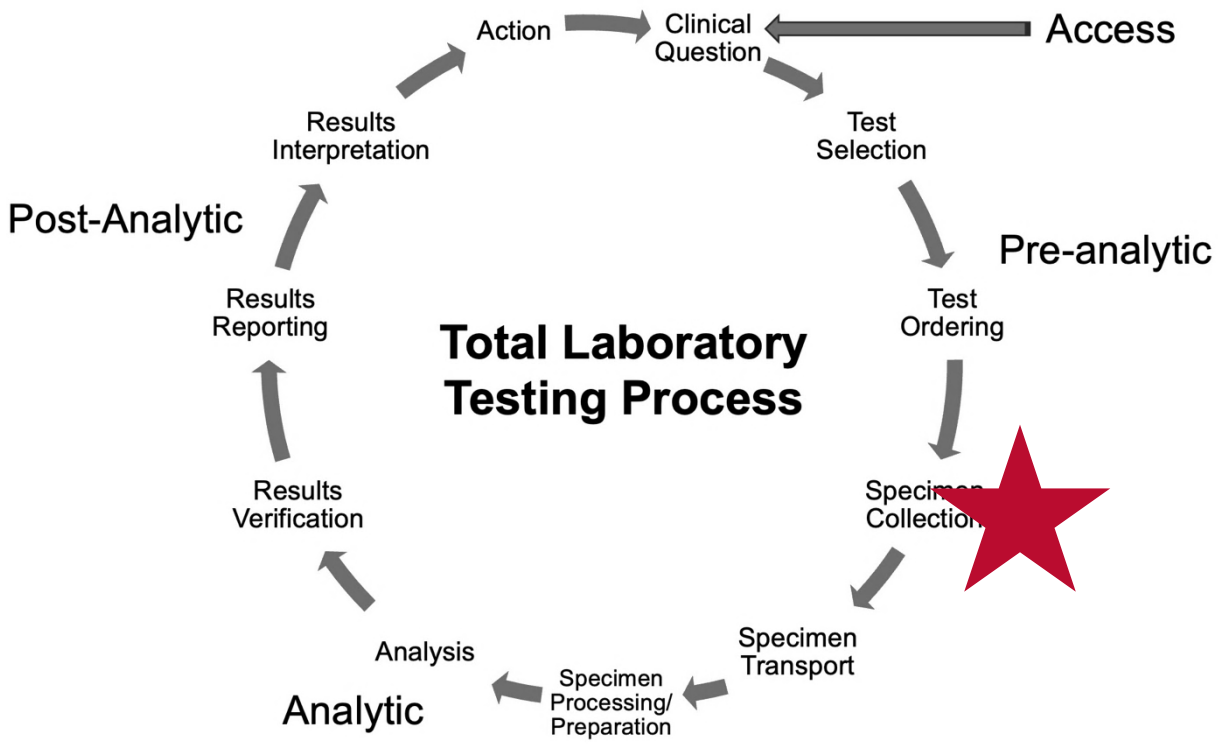


Robotic Venipuncture

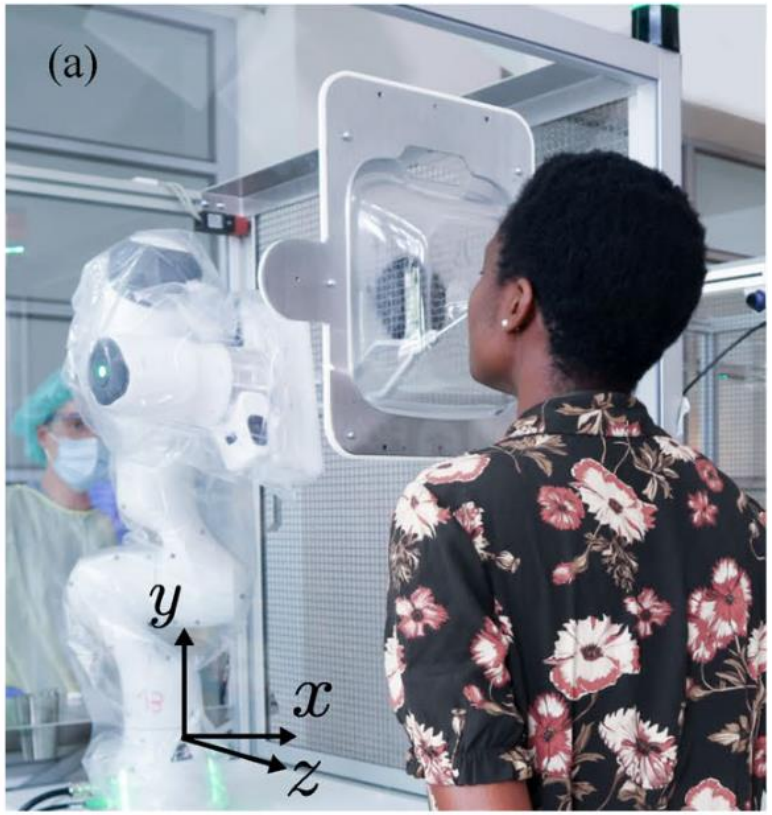


Leipheimer JM 2019 Technology 07:98–107.

AI Opportunities Throughout The Testing Process

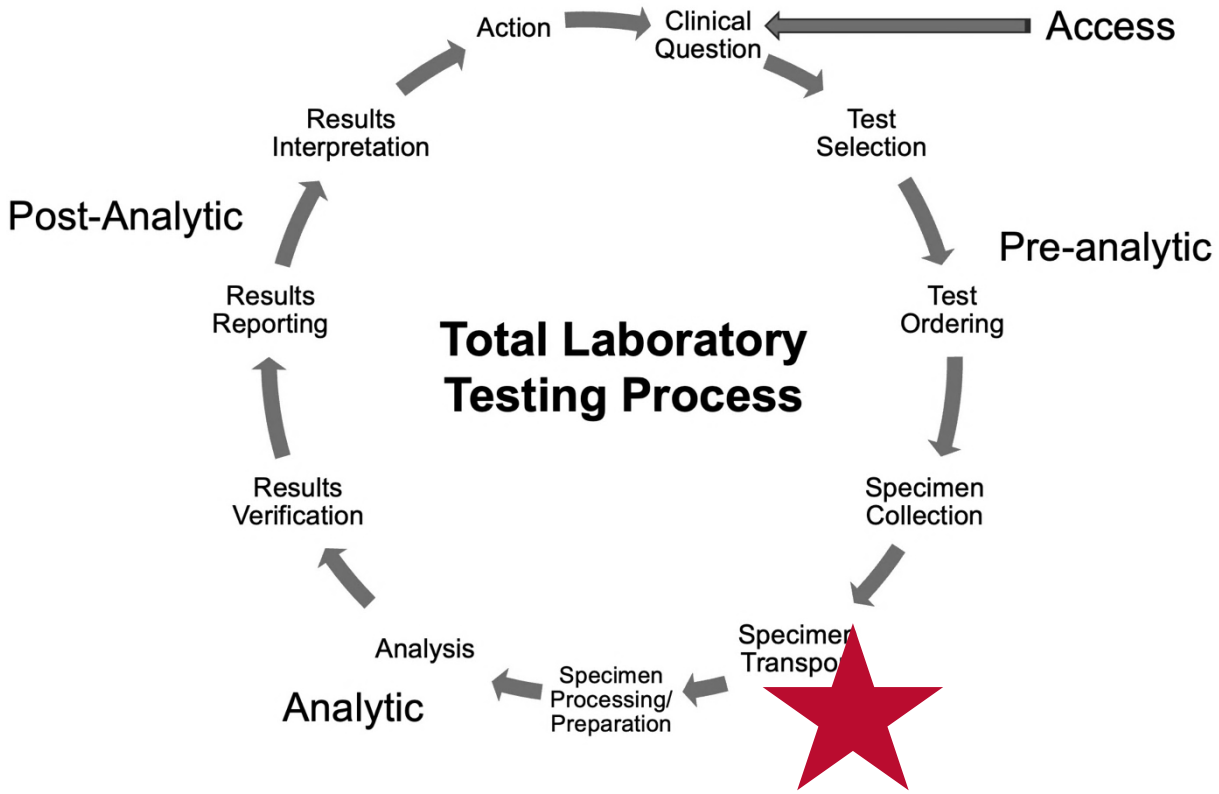


Nasopharyngeal Swab



Haddadin S 2024 Sci Rep 14:142 PMID: 38167977

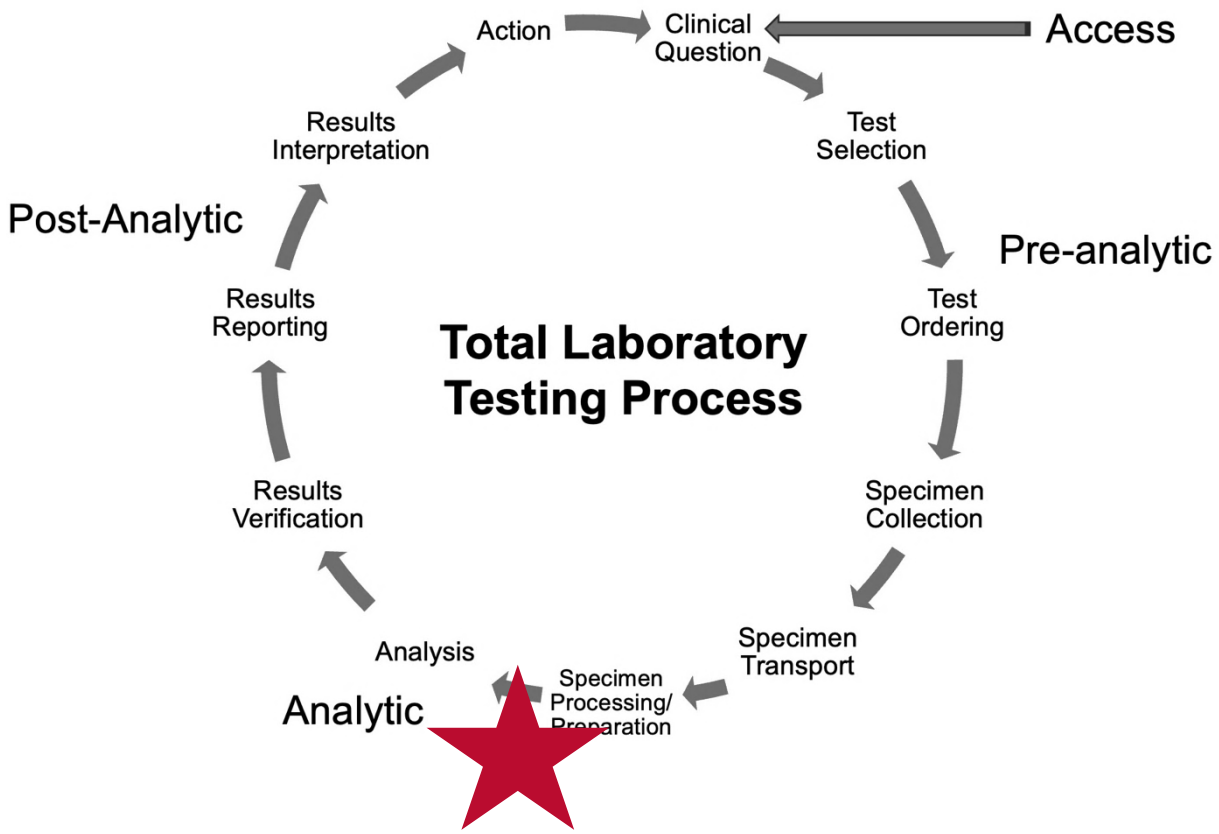
AI Opportunities Throughout The Testing Process

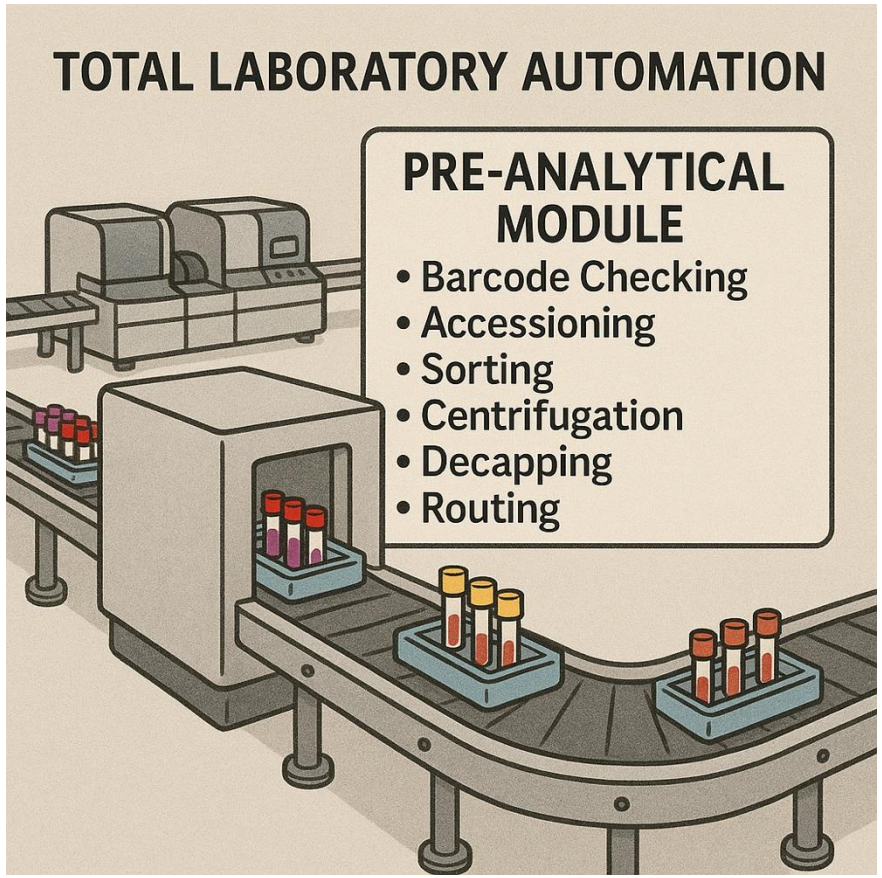


Drone-based Specimen Transport



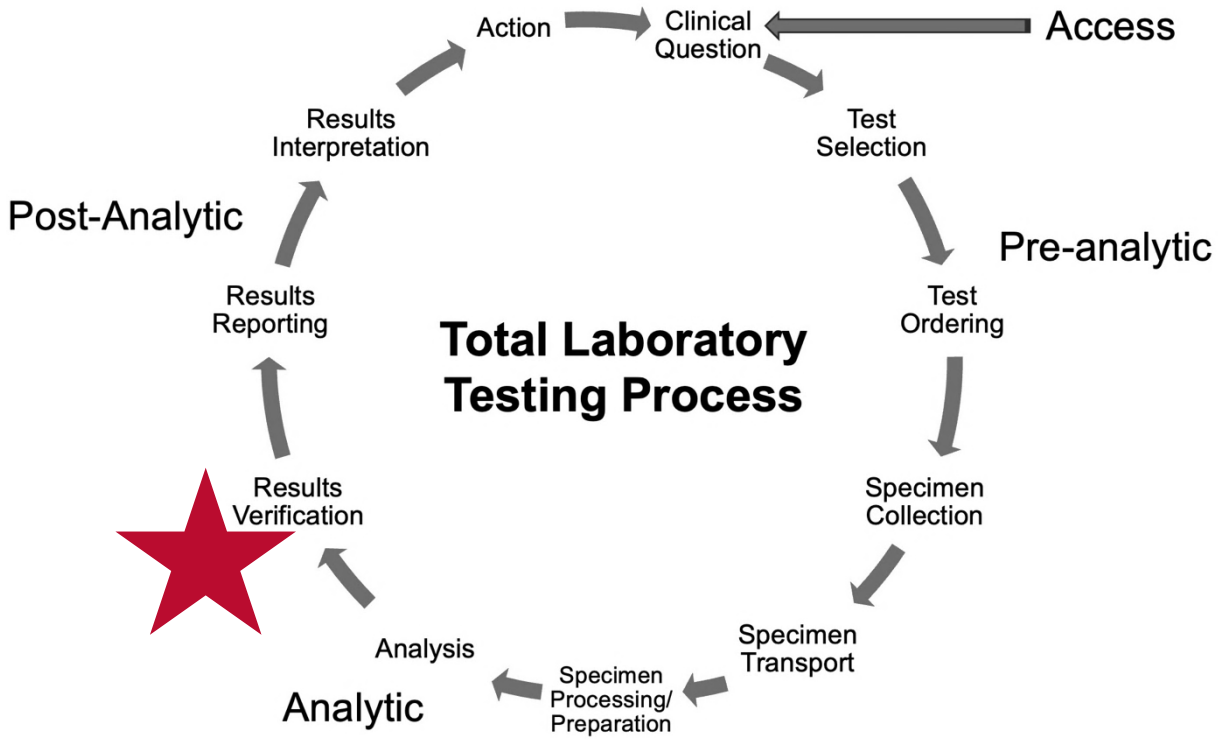
AI Opportunities Throughout The Testing Process

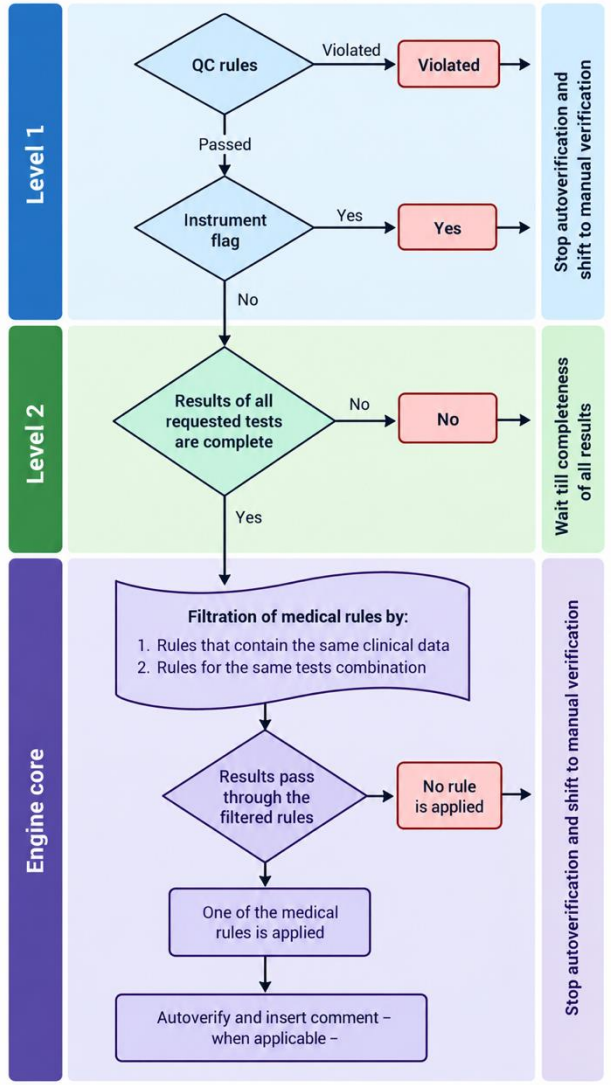




LIPPI G, DA RIN G. CLIN CHEM LAB MED. 2019. DOI: 10.1515/CCLM-2018-1323.

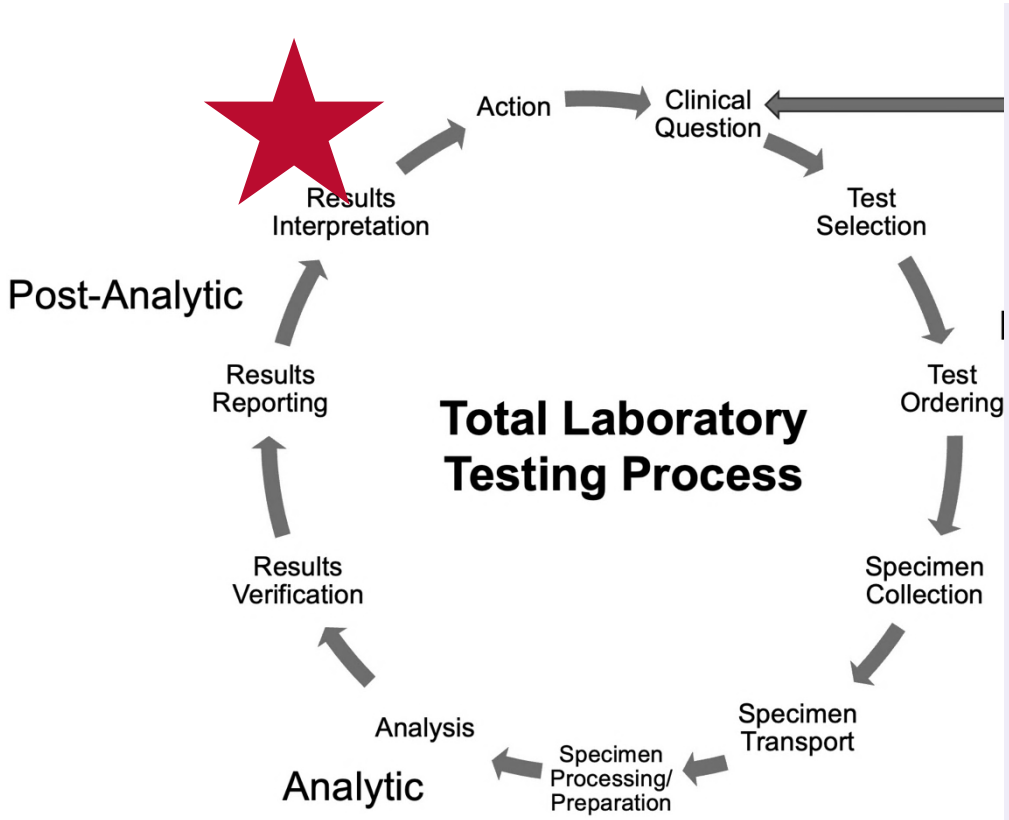
AI Opportunities Throughout The Testing Process





ADAPTED FROM SEDIQ, AMANY MOHYELDIN AND AHMAD GABALLAHM HALA ABDEL-AZEEZ. *ANNALS OF SAUDI MEDICINE* 34 (2014): 427 - 432.

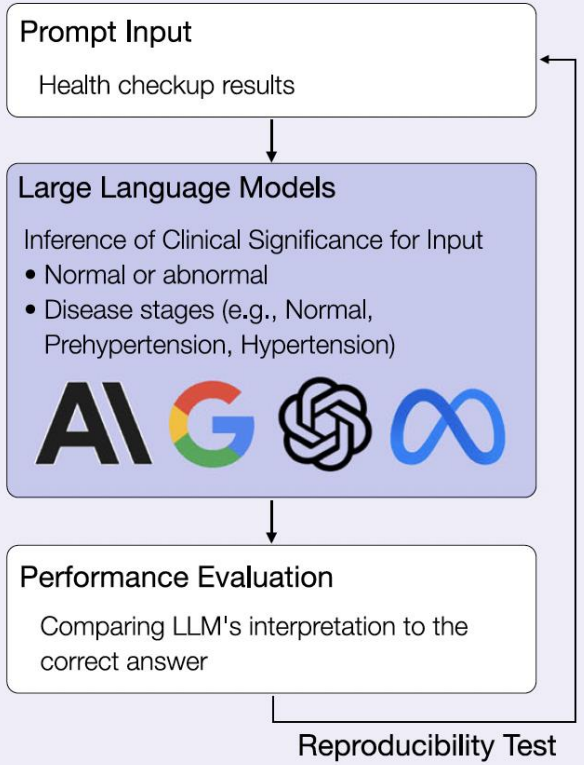
AI Opportunities Throughout The Testing Process



Example of Prompt

Instruction
Role: Health Screening Data Interpreter
Objective: Analyze the patient's health screening data and generate a structured JSON format report. (JSON format: Key – Analysis Item, Value – Result Interpretation)
Example
Input: A table containing numerical data on various items such as gender, blood pressure, cholesterol, blood glucose, etc.
Output: A report of results interpreted based on thresholds for BMI, blood pressure, cholesterol, etc.
Reference values
[Screening Item]
< Normal Range >: Normal
< Abnormal Range >: Abnormal
Question
Please interpret the data for this patient.
Input: A table containing numerical data on various items such as gender, blood pressure, cholesterol, blood glucose, etc.

Performance Evaluation



YOU, J., SHIN, H. *NPJ DIGIT. MED.* **9**, 565 (2026). HTTPS://DOI.ORG/10.1038/S41746-026-02467-Y

IV Fluid Contamination Detection as an AI Opportunity

- Introduction of exogenous intravenous fluid at collection
- Interferes with downstream laboratory testing

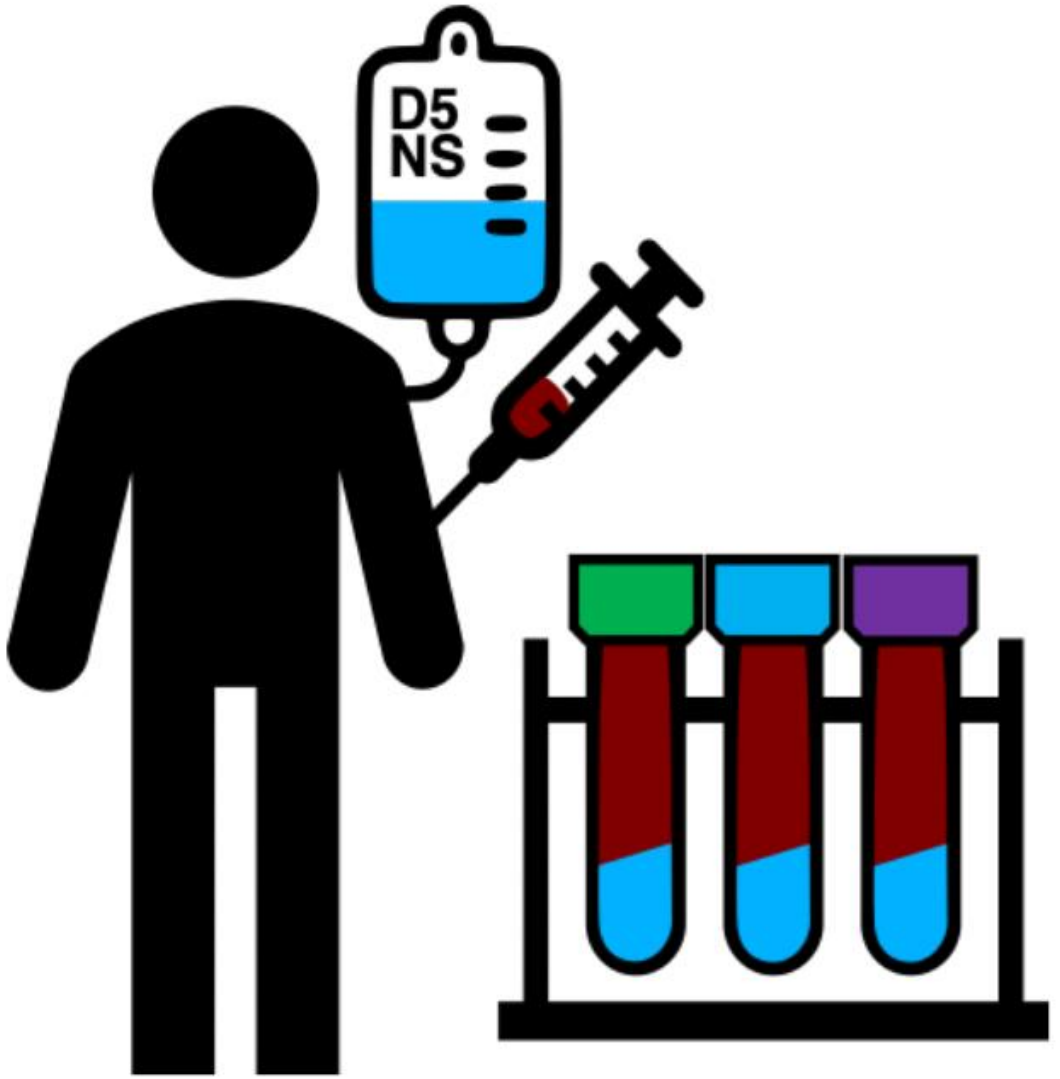


Image courtesy of Nick Spies

Undetected IV Fluid Contamination Harms Patients

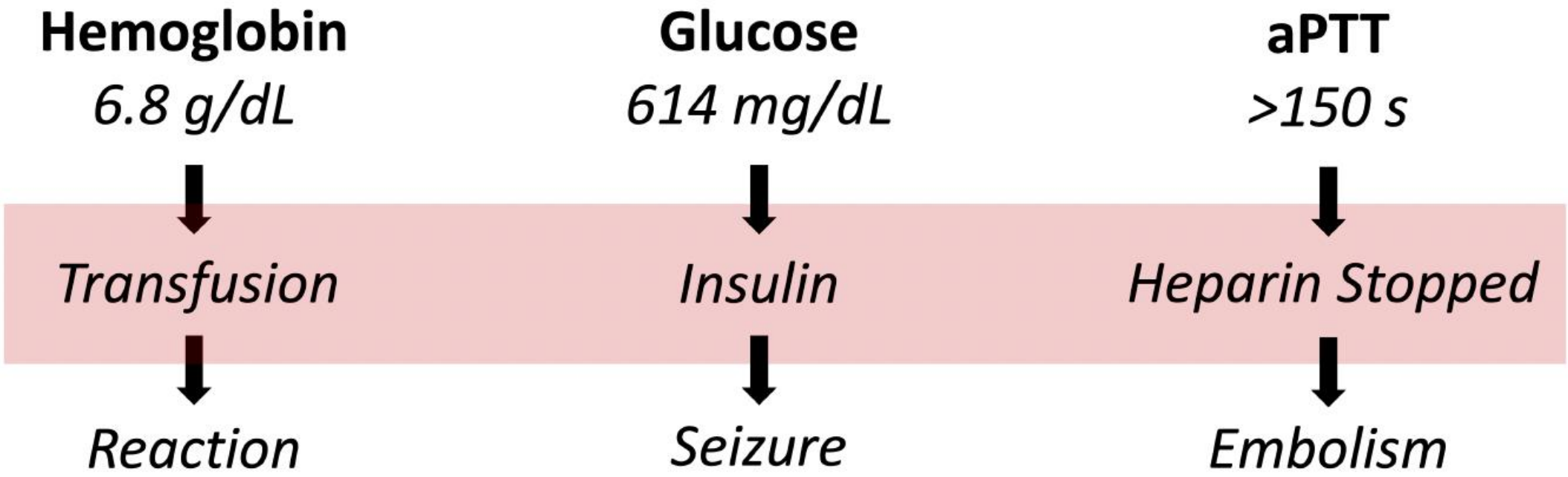
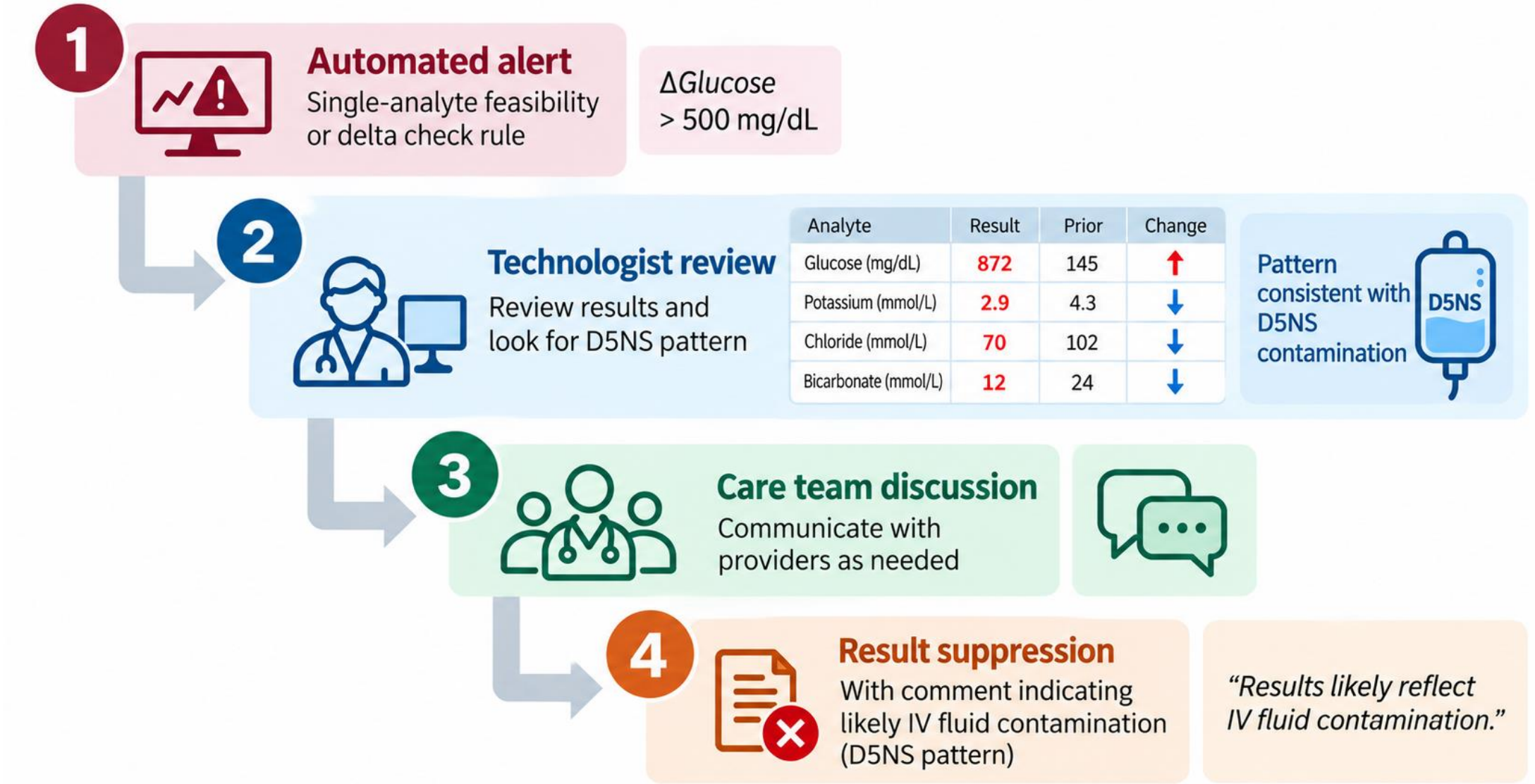


Figure and cases courtesy of Nick Spies

IV Fluid Contamination Relies on Human Review



Process at Barnes-Jewish Hospital (Saint Lous, MO, USA)

IMAGE GENERATED WITH CHATGPT

Which of These BMPs Was Contaminated?

A

Analyte	Prior	Current
Na (mmol/L)	133.0	139.0
K (mmol/L)	4.8	2.9
Ca (mg/dL)	8.3	5.7
Cl (mmol/L)	96.0	114.0
Cr (mg/dL)	0.63	0.50
BUN (mg/dL)	6.0	6.0
CO_2 (mmol/L)	18.0	20.0
Glucose (mg/dL)	68.0	48.0

B

Analyte	Prior	Current
Na (mmol/L)	132.0	143.0
K (mmol/L)	6.2	7.6
Ca (mg/dL)	9.5	13.4
Cl (mmol/L)	95.0	96.0
Cr (mg/dL)	1.23	0.47
BUN (mg/dL)	61.0	27.0
CO_2 (mmol/L)	19.0	28.0
Glucose (mg/dL)	267	1122.0

C

Analyte	Prior	Current
Na (mmol/L)	133.0	139.0
K (mmol/L)	4.6	3.9
Ca (mg/dL)	9.0	7.8
Cl (mmol/L)	96.0	104.0
Cr (mg/dL)	7.59	7.64
BUN (mg/dL)	46.0	51.0
CO_2 (mmol/L)	23.0	19.0
Glucose (mg/dL)	103.0	103.0

IMAGE GENERATED WITH CHATGPT

Which of These BMPs Was Contaminated?

A

Analyte	Prior	Current
Na (mmol/L)	133.0	139.0
K (mmol/L)	4.8	2.9
Ca (mg/dL)	8.3	5.7
Cl (mmol/L)	96.0	114.0
Cr (mg/dL)	0.63	0.50
BUN (mg/dL)	6.0	6.0
CO_2 (mmol/L)	18.0	20.0
Glucose (mg/dL)	68.0	48.0



25% NS contamination

Expected pattern:
↓ K, ↓ Ca, ↑ Cl
(mild ↑ Na)

B

Analyte	Prior	Current
Na (mmol/L)	132.0	143.0
K (mmol/L)	6.2	7.6
Ca (mg/dL)	9.5	13.4
Cl (mmol/L)	95.0	96.0
Cr (mg/dL)	1.23	0.47
BUN (mg/dL)	61.0	27.0
CO_2 (mmol/L)	19.0	28.0
Glucose (mg/dL)	267	1122.0



15% D5LR contamination

Expected pattern:
↑ glucose, ↑ K, ↑ Ca,
↑ CO_2 (HCO_3^-),
minimal change in Cl

C

Analyte	Prior	Current
Na (mmol/L)	133.0	139.0
K (mmol/L)	4.6	3.9
Ca (mg/dL)	9.0	7.8
Cl (mmol/L)	96.0	104.0
Cr (mg/dL)	7.59	7.64
BUN (mg/dL)	46.0	51.0
CO_2 (mmol/L)	23.0	19.0
Glucose (mg/dL)	103.0	103.0



11% NS contamination

Expected pattern:
↓ K, ↓ Ca, ↑ Cl
(mild ↑ Na)

IMAGE GENERATED WITH CHATGPT

IV Fluid Contamination as a Target for AI Application



Nick Spies, MD

> *Can artificial intelligence improve the clinical detection of intravenous fluid contamination?*

Expert Systems Encode Expertise as Explicit Rules

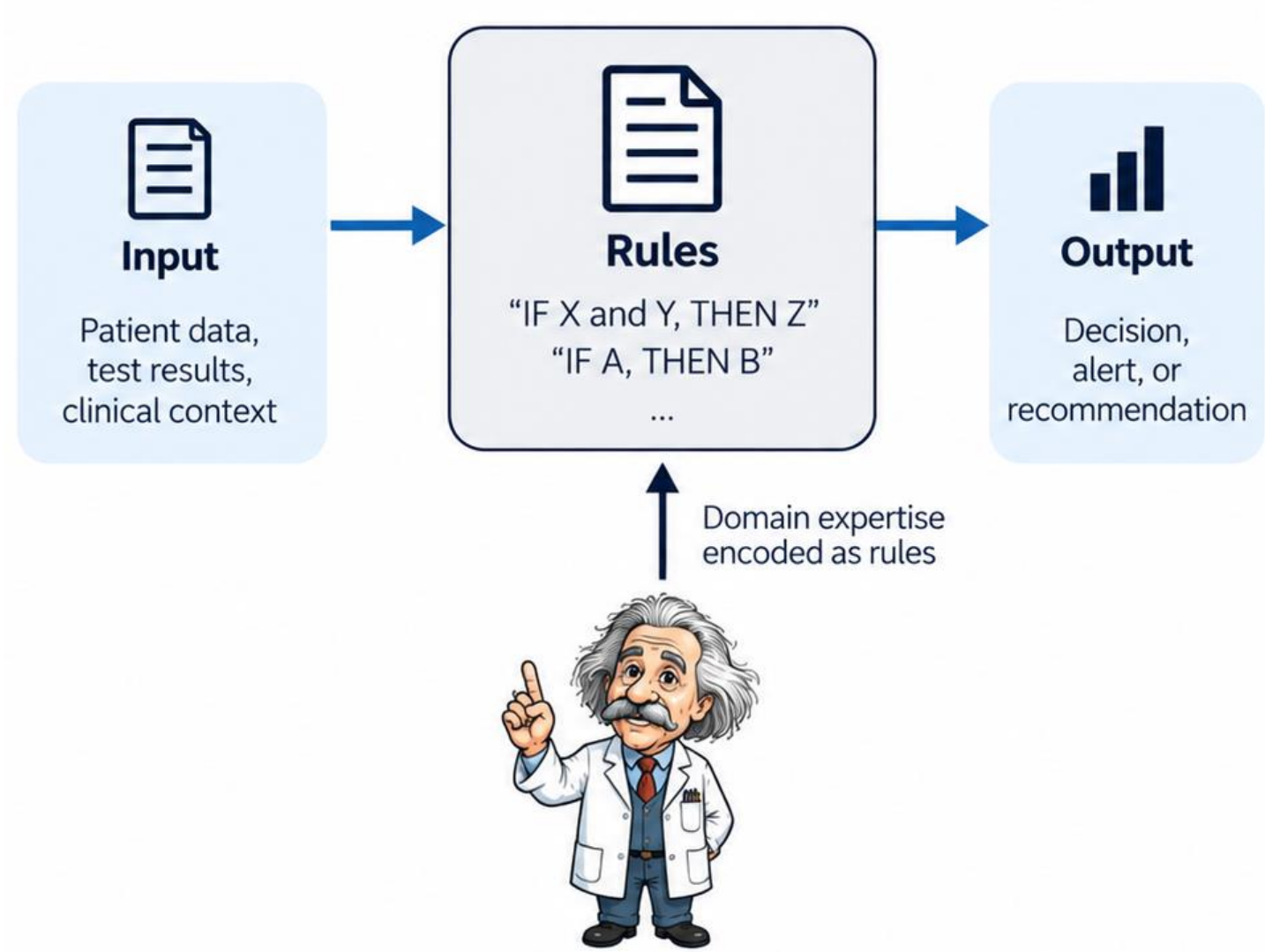
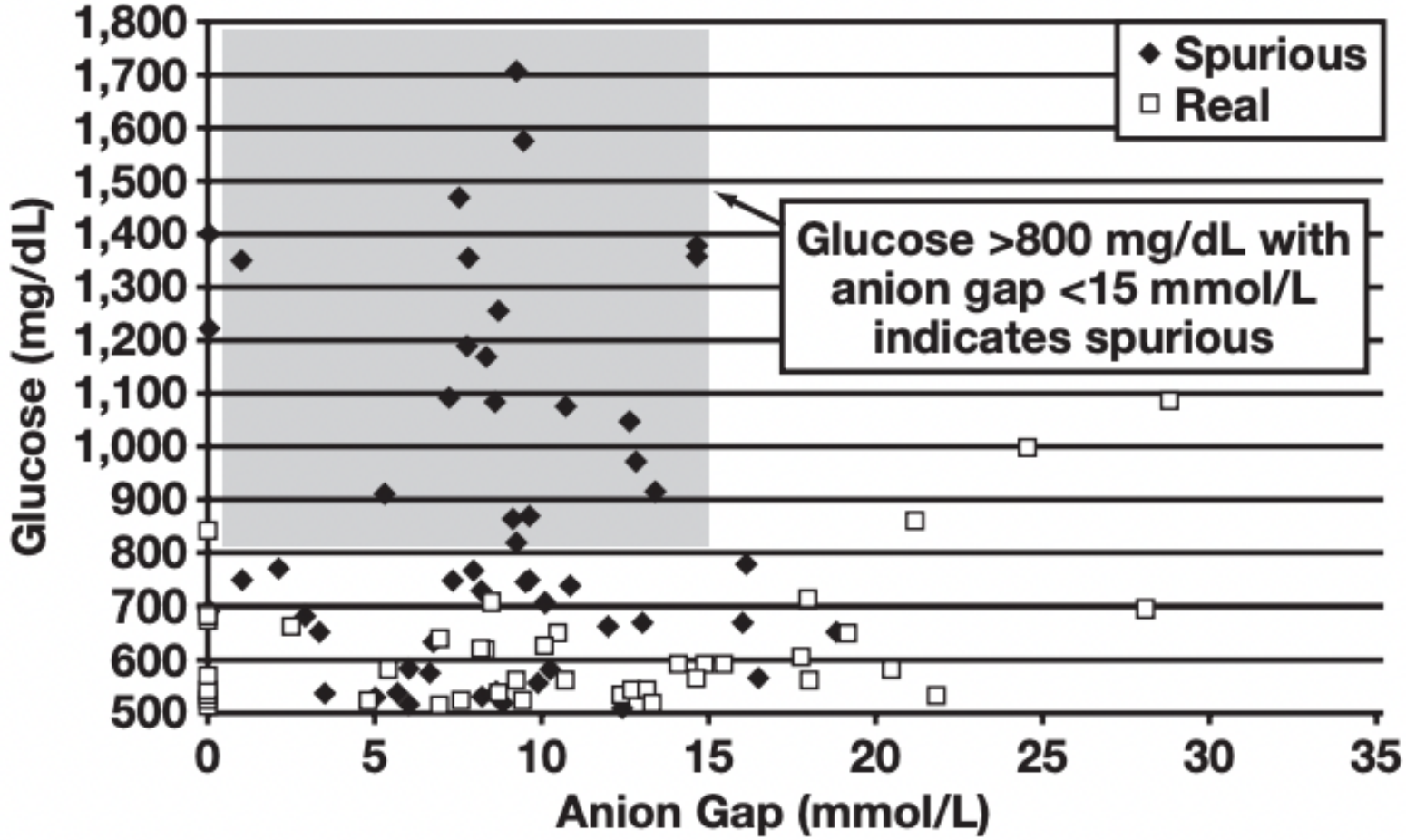


IMAGE GENERATED WITH CHATGPT

Expert System for Dextrose Fluid Contamination



Rules

If glucose > 800 mg/dL
AND anion gap < 15 mmol/L

Then

'Spurious'

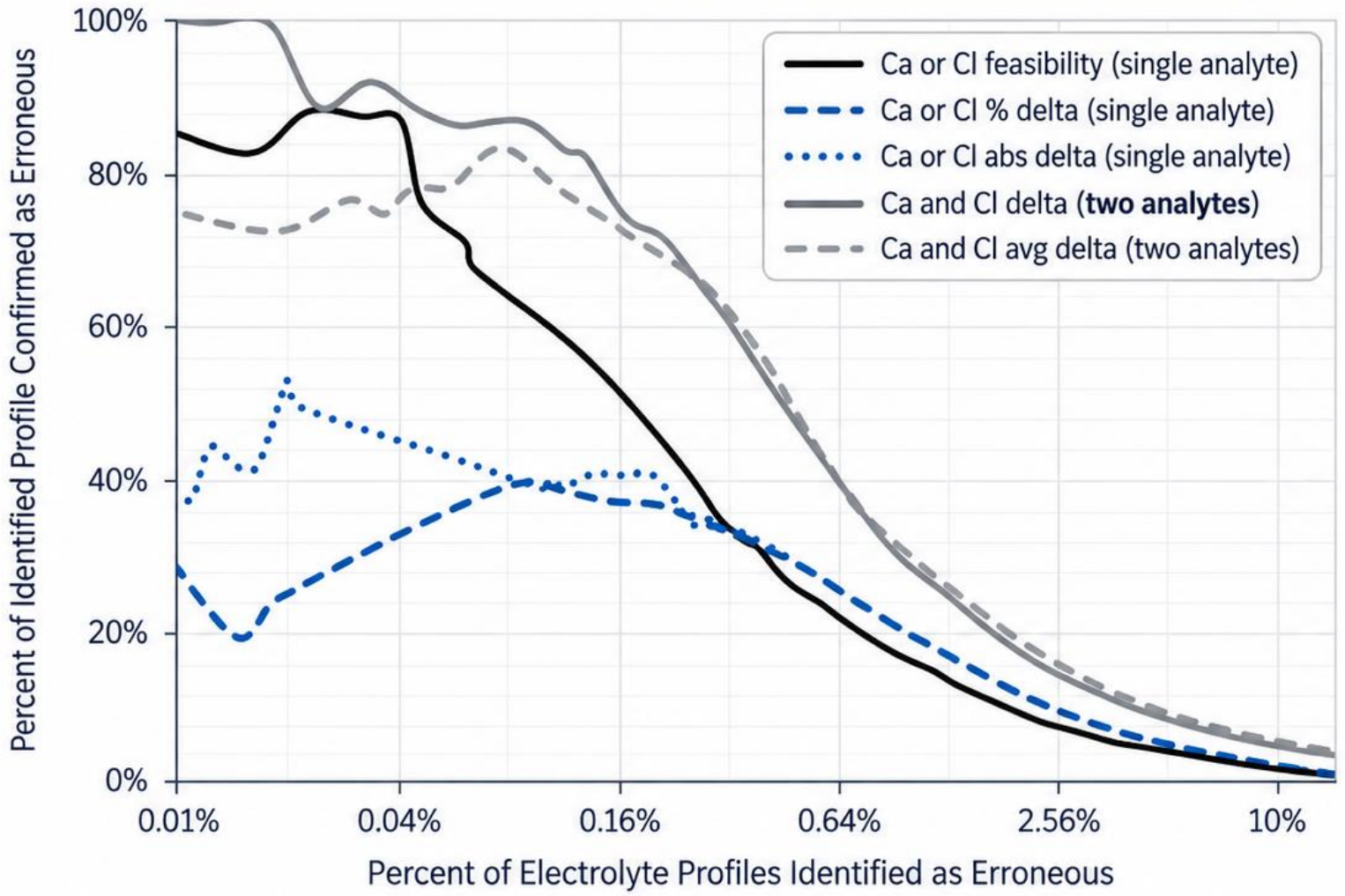
Else

'Real'

Gold standard: Expert chart review

Baron 2012 Am J Clin Pathol PMID: 22912358

Expert Systems For NS Contamination Detection



Method 4

If (Ca delta > cutoff
and Cl delta > cutoff)

Then → Contaminated

Else → Not Contaminated

Method 5

If AVG(Ca delta, Cl delta) > cutoff

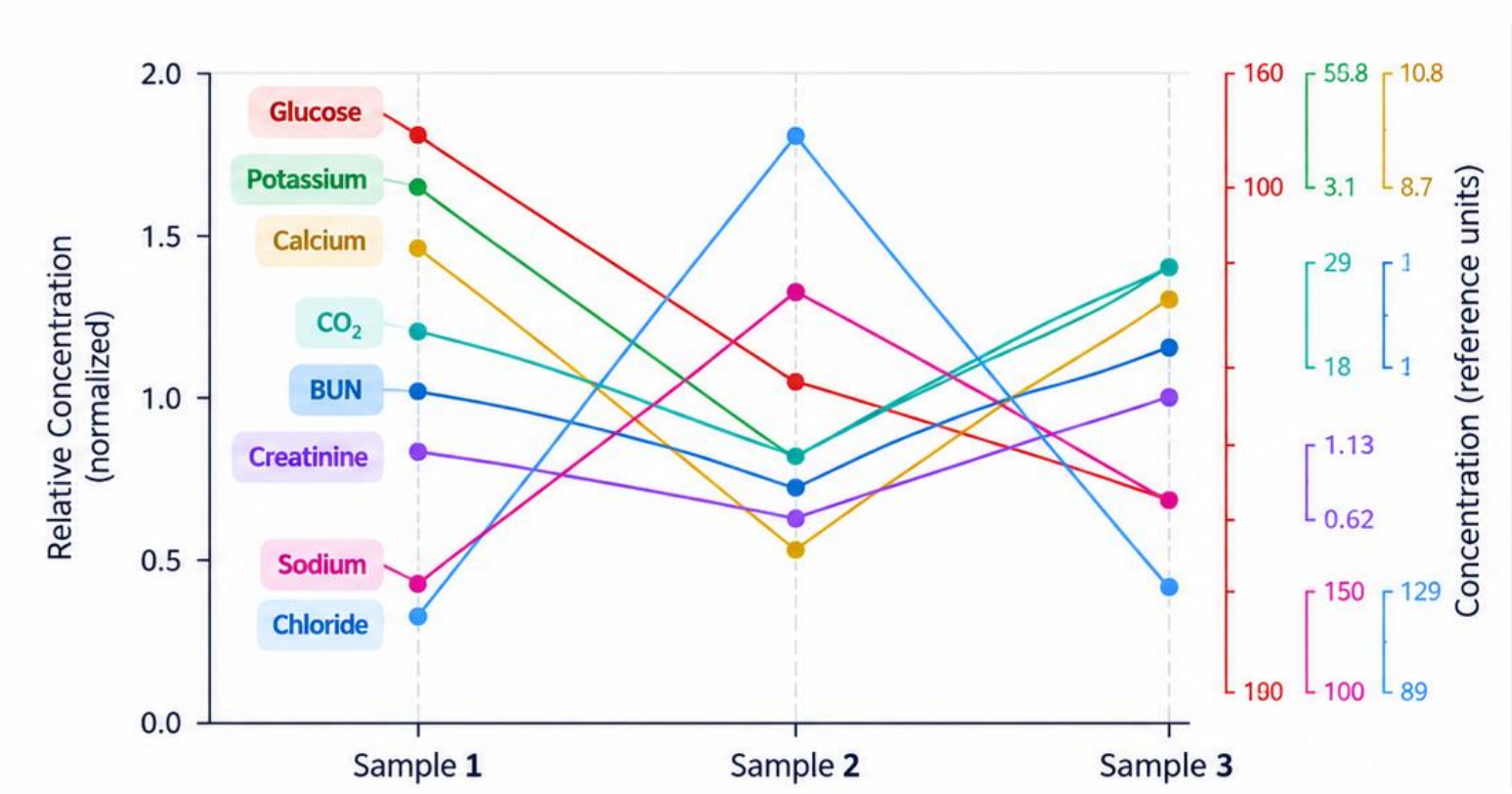
Then → Contaminated

Else → Not Contaminated

Gold standard: anomaly resolves on next sample

Figure Recreated from Patel 2015 Clin Chem Lab Med PMID: 25719332

Expert System for Multifluid Detection



Rules

$NS_{10\%}$

$\Delta Cl > 7.7$, $\Delta K > -0.7$ and $\Delta Ca > -1.7$

$LR_{10\%}$

$\Delta Glu > -11.3$, $\Delta Ca > -0.7$ and $\Delta CO_2 > -3.3$

$D5W_{10\%}$

$\Delta Glu > 534$, $\Delta Cl > -13.9$ and $\Delta Na > -16.7$

Gold standard:

1. Anomaly with resolution pattern
2. Evidence of suspected fluid administration w/in 24 hours

Recreated from Choucair 2023 Clinica Chimica Acta PMID: 36309069

Expert Systems for IV Fluid Contamination Detection



Simple, transparent systems

Rule-based expert systems are easy to understand and implement.



Achieve moderate accuracy

Effective at identifying many contaminated samples, with moderate performance.



Rule sets become large

When chasing higher accuracy and broader fluid coverage, rule sets can become complex and difficult to maintain.

IMAGE GENERATED WITH CHATGPT

IV Fluid Contamination as a Target for Machine Learning



Nick Spies, MD

Can machine learning improve the detection of IV fluid contamination?

ML Leverages Data Instead of Human Expertise

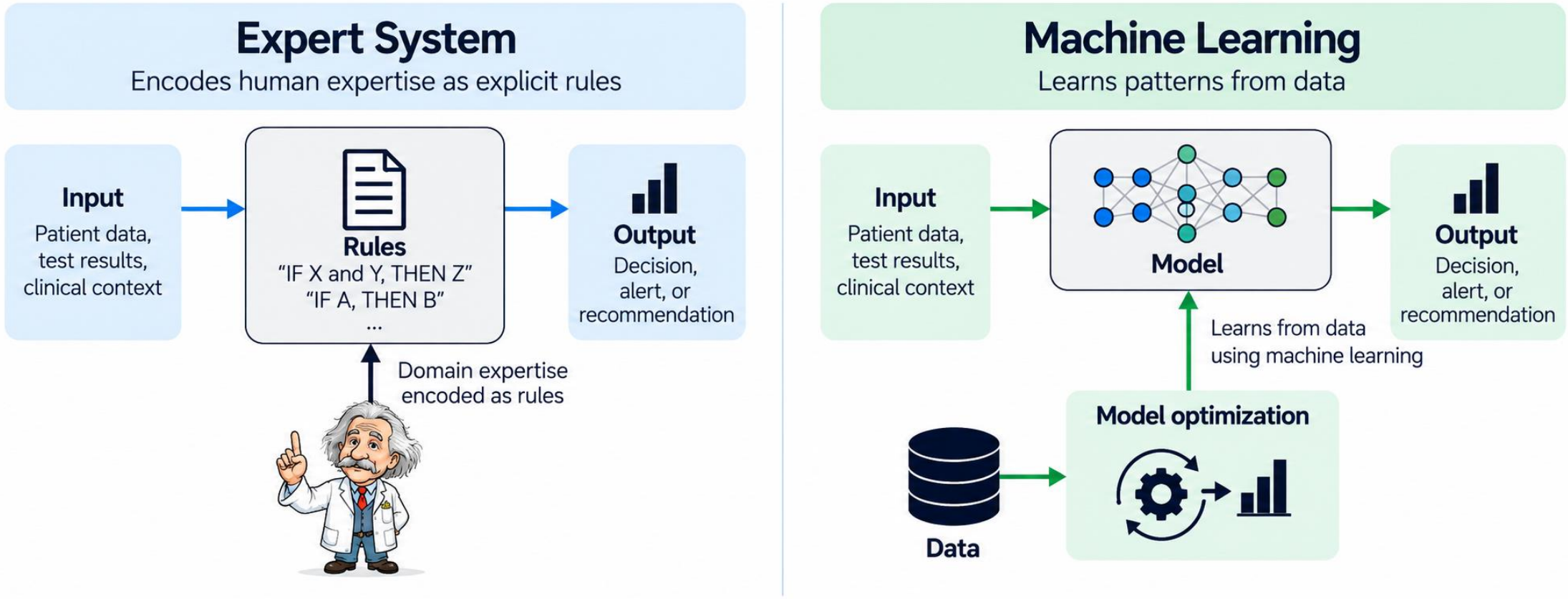
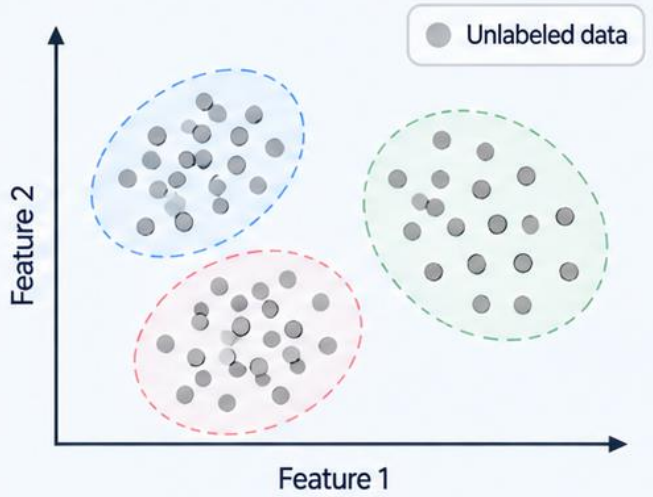


IMAGE GENERATED WITH CHATGPT

ML Approaches Vary in Data Label Requirements

Unsupervised Learning

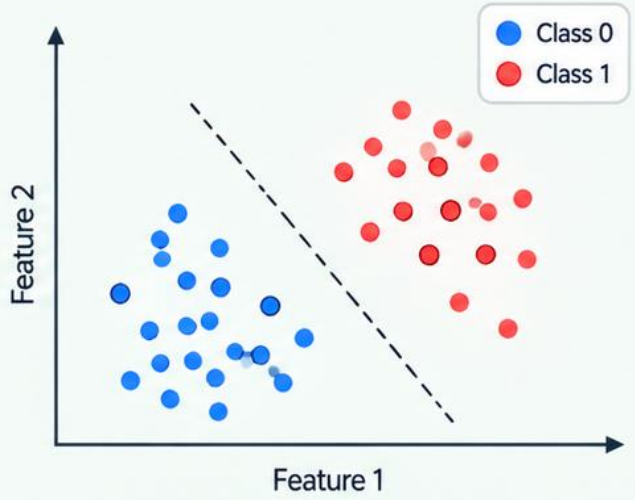
Finds patterns in data without labeled outcomes



Examples: clustering, anomaly detection, dimensionality reduction

Supervised Learning

Learns from labeled data to predict an outcome



Examples: classification (e.g., logistic regression, random forest), regression (e.g., linear regression)

IMAGE GENERATED WITH CHATGPT

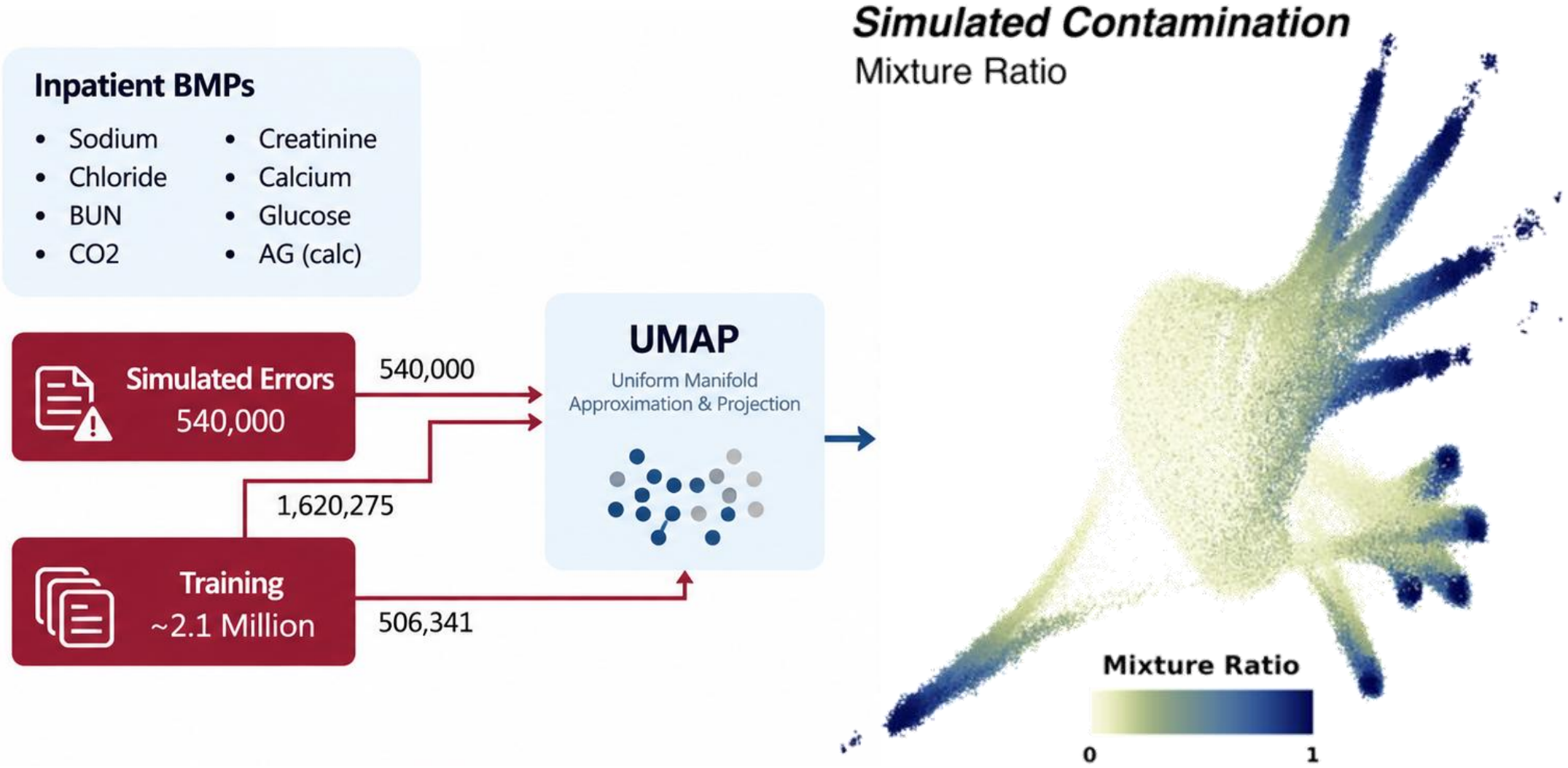
IV Fluid Contamination as a Target for Unsupervised ML



Nick Spies, MD

Can unsupervised ML improve the detection of IV fluid contamination?

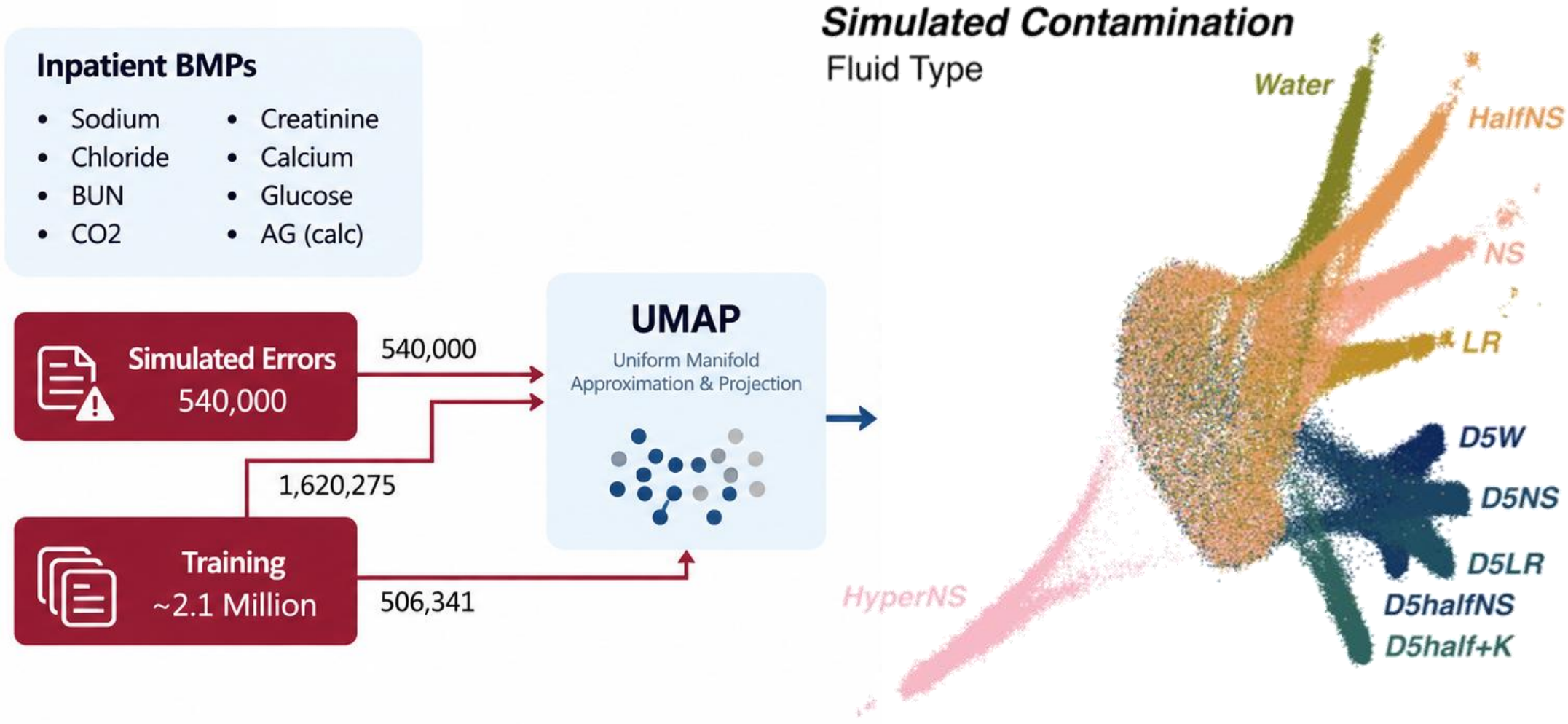
Unsupervised ML to Detect Anomalous BMP Results



Spies et. al. Clin Chem. 2024 Feb 7;70(2):444-452. PMID: 38084963.

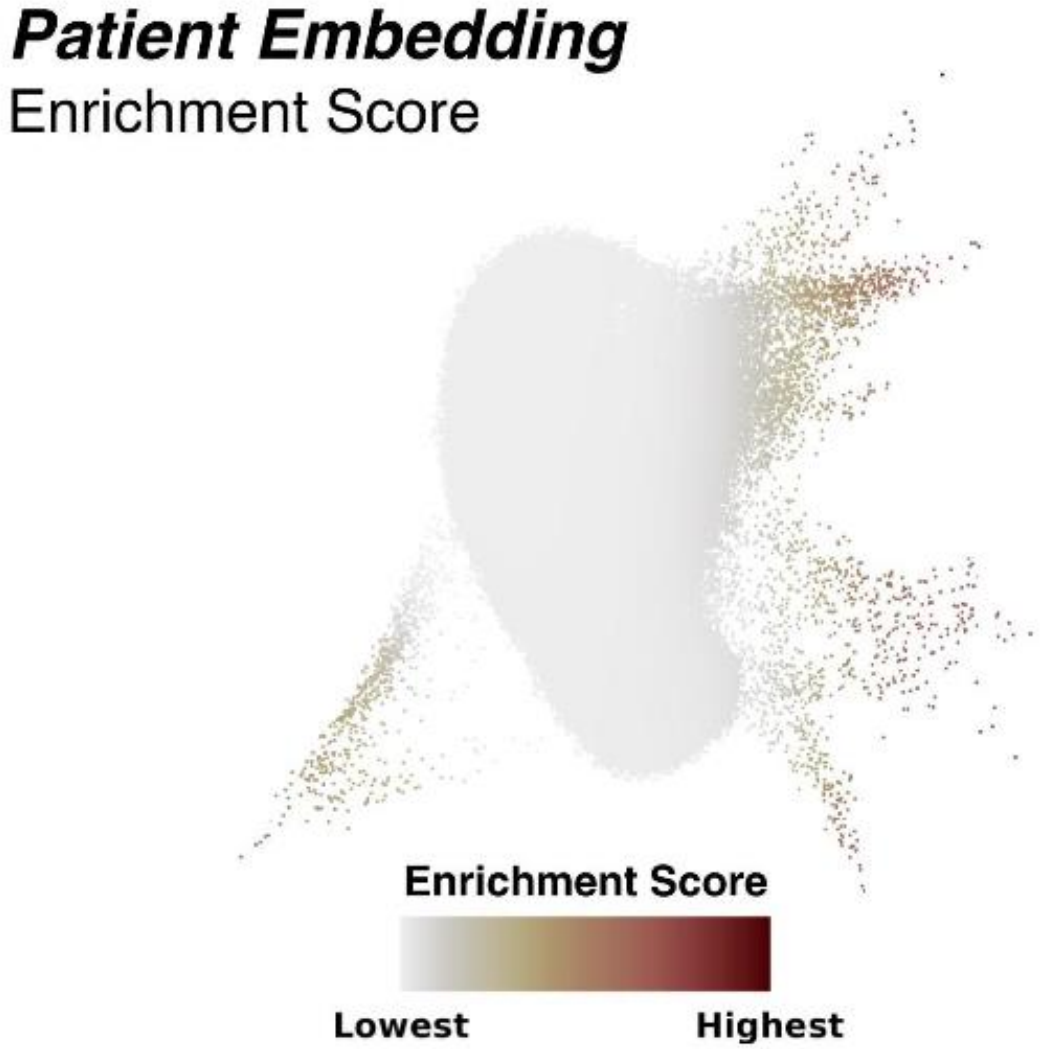
UMAP: MCINNES 2018 JOURNAL OF OPEN SOURCE SOFTWARE HTTPS://DOI.ORG/10.21105/JOSS.00861

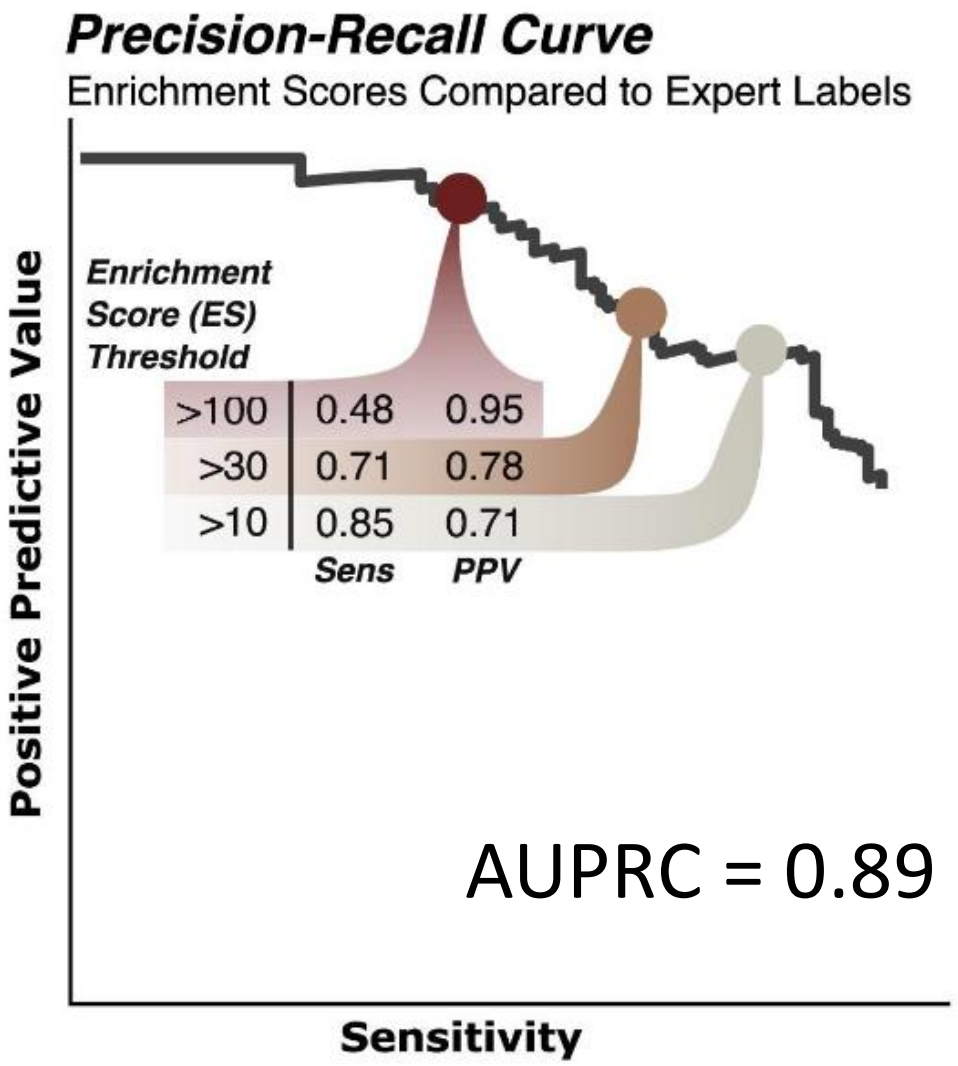
Unsupervised ML to Detect Anomalous BMP Results



UMAP: MCINNES 2018 JOURNAL OF OPEN SOURCE SOFTWARE HTTPS://DOI.ORG/10.21105/JOSS.00861

Leveraging Unsupervised Model to Classify Patient Results

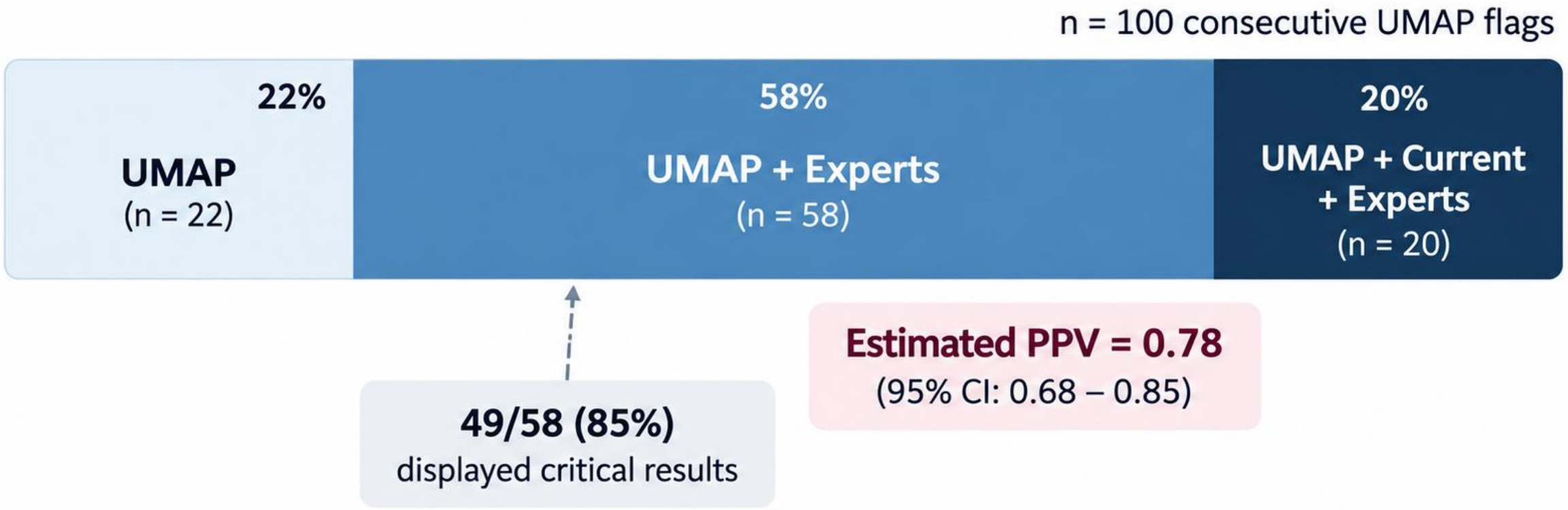




AUPRC = 0.89

Gold standard: consensus of experts

UMAP Detects Additional Clinically Meaningful Contamination



Gold standard: consensus of experts

IMAGE GENERATED WITH CHATGPT

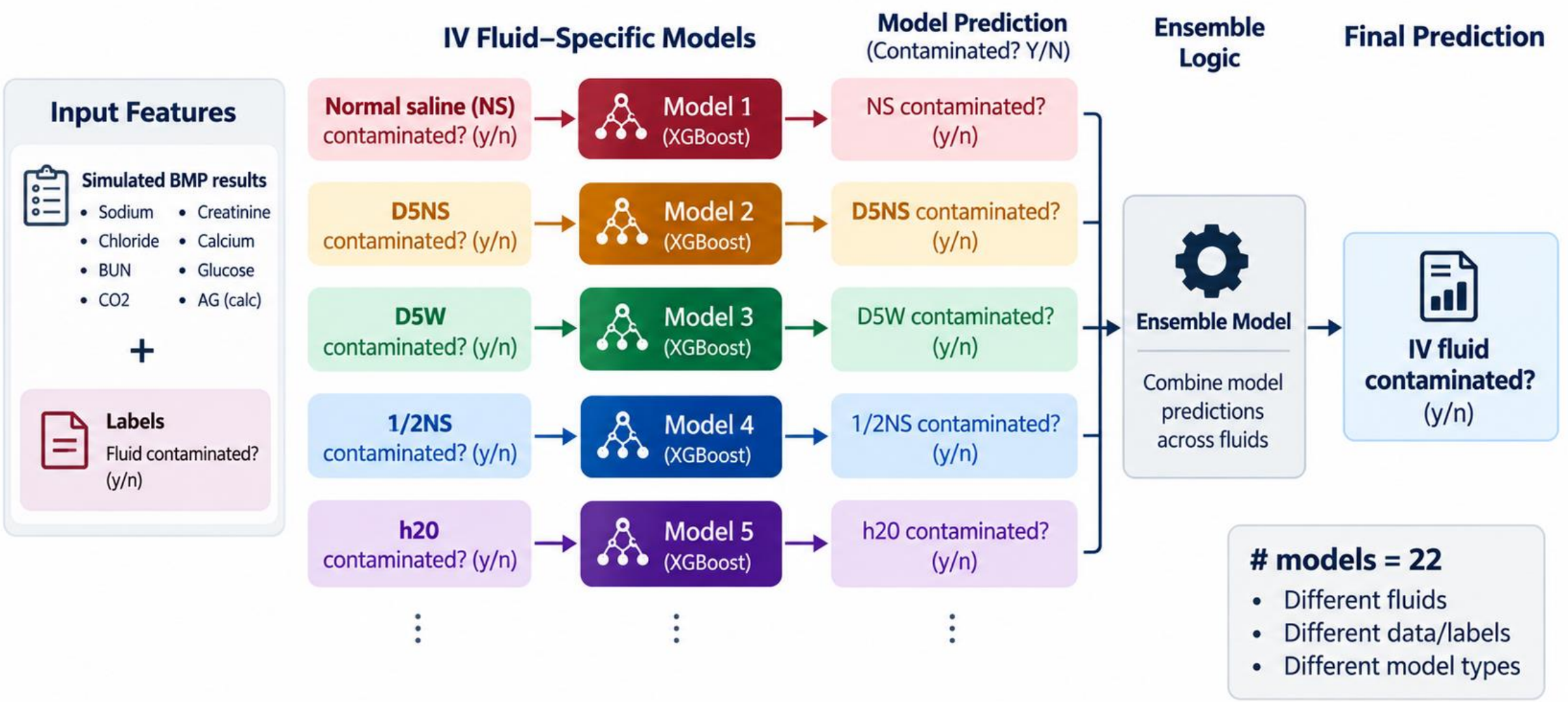
IV Fluid Contamination as a Target for Unsupervised ML



Nick Spies, MD

Can supervised ML further improve the detection of IV fluid contamination?

Ensembled ML for IV Fluid Contamination Detection



Spies 2025 Clin Chem PMID: 39545815

IMAGE GENERATED WITH CHATGPT

Methods

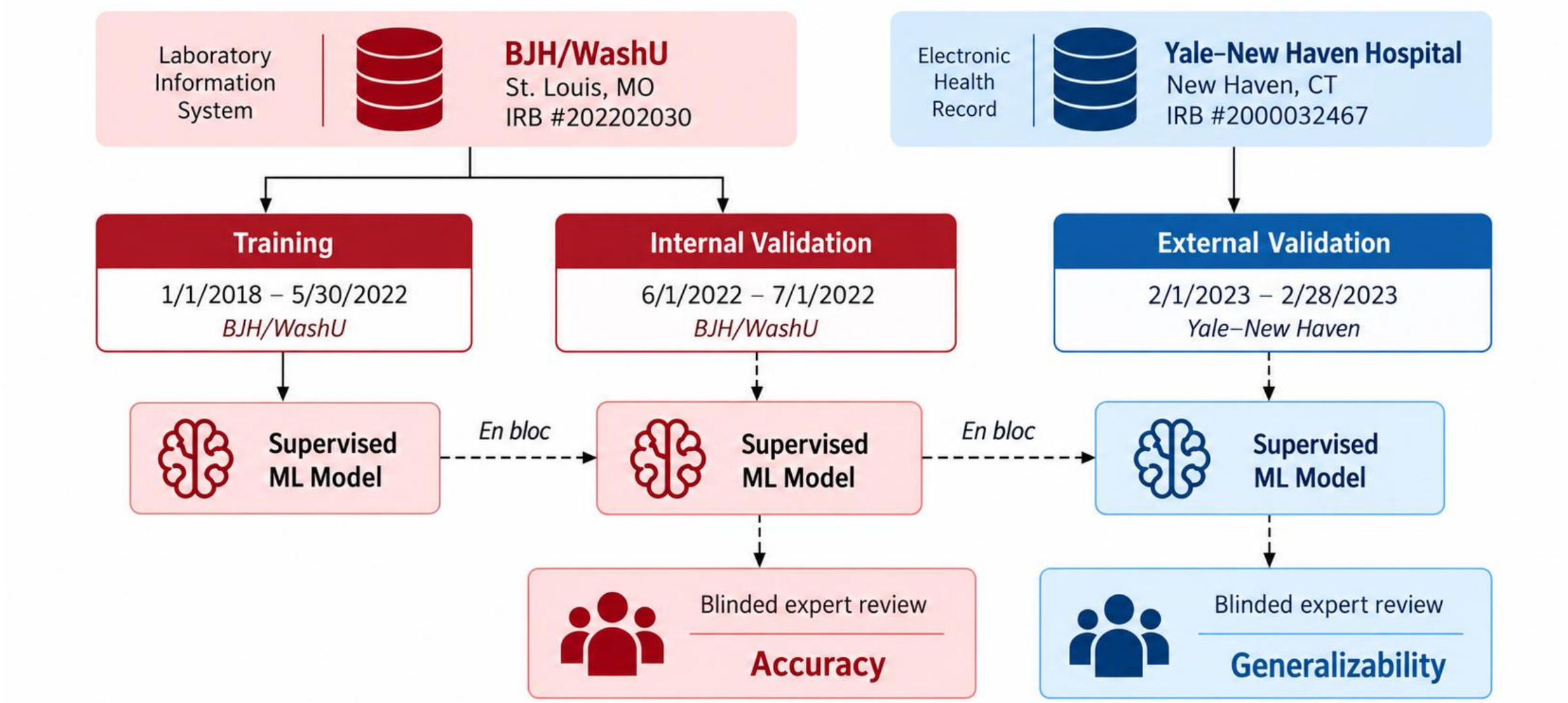


IMAGE GENERATED WITH CHATGPT

Spies 2025 Clin Chem PMID: 39545815

Supervised ML Models are Accurate and Generalizable

Internal Validation (WashU)

Blinded expert review
(gold standard)

BJC/WashU
St. Louis, MO

Sensitivity	0.858
Specificity	0.993
PPV	0.657
NPV	0.998
Accuracy	0.99

External Validation (Yale)

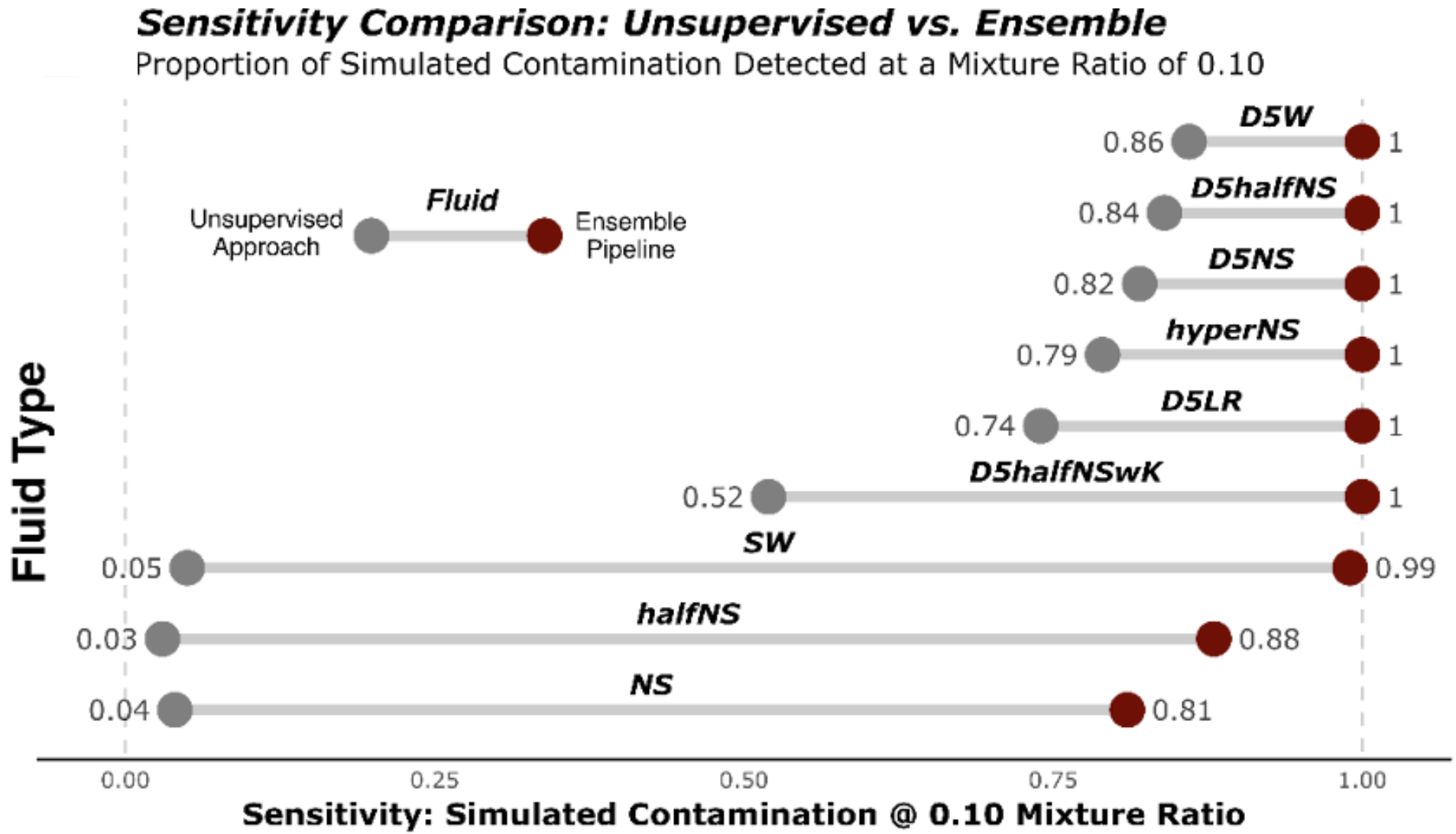
Blinded expert review
(gold standard)

Yale–New Haven Hospital
New Haven, CT

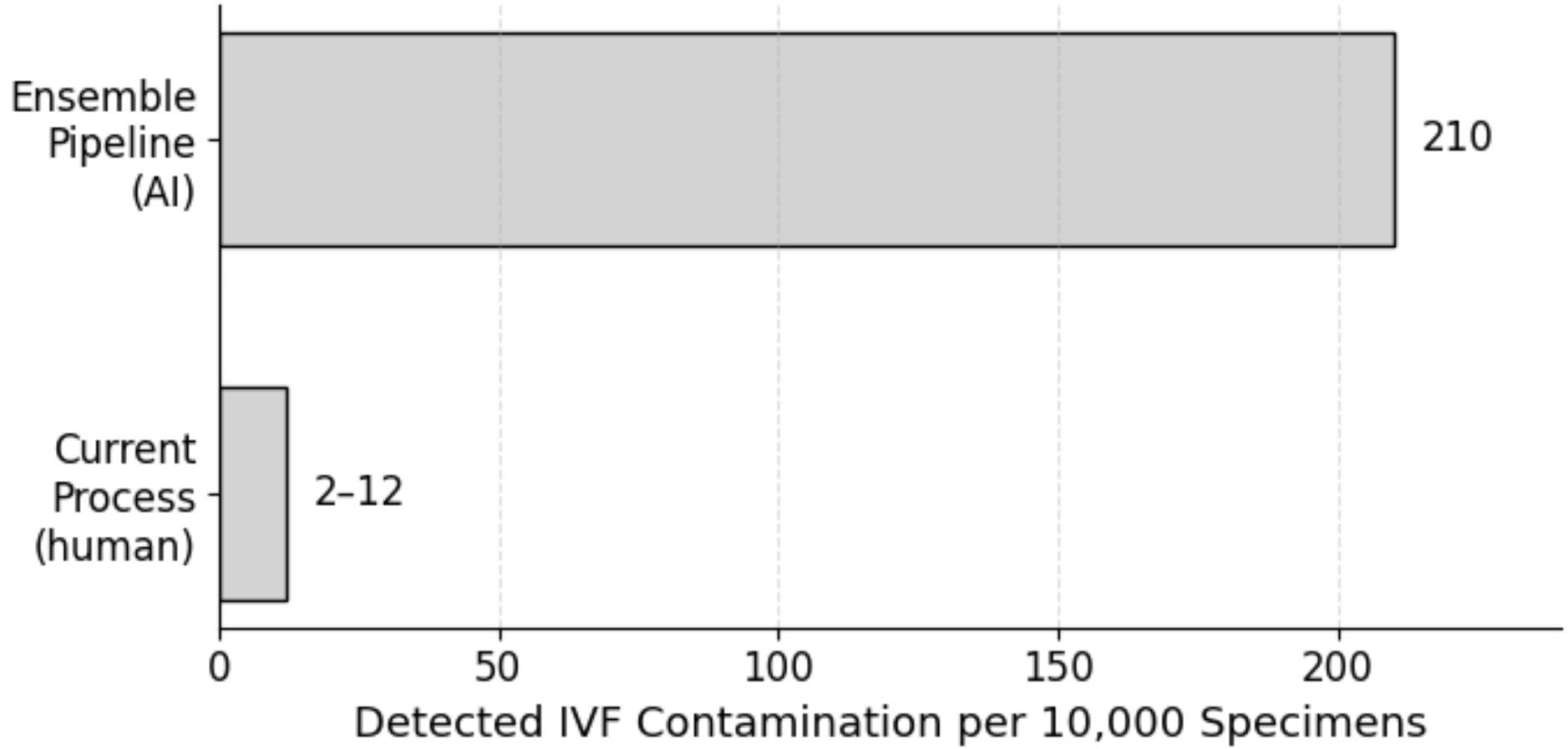
Sensitivity	1.000
Specificity	0.980
PPV	0.153
NPV	1.000
Accuracy	0.980

IMAGE GENERATED WITH CHATGPT

Ensembled Supervised ML Further Improves Sensitivity



Ensemble Method Increases Contamination Flagging



IV Fluid Contamination is Only Rarely Detected in Practice



Sciacovelli 2019 Clin Chim Acta PMID: 31295446

Machine Learning for IV Fluid Contamination Detection

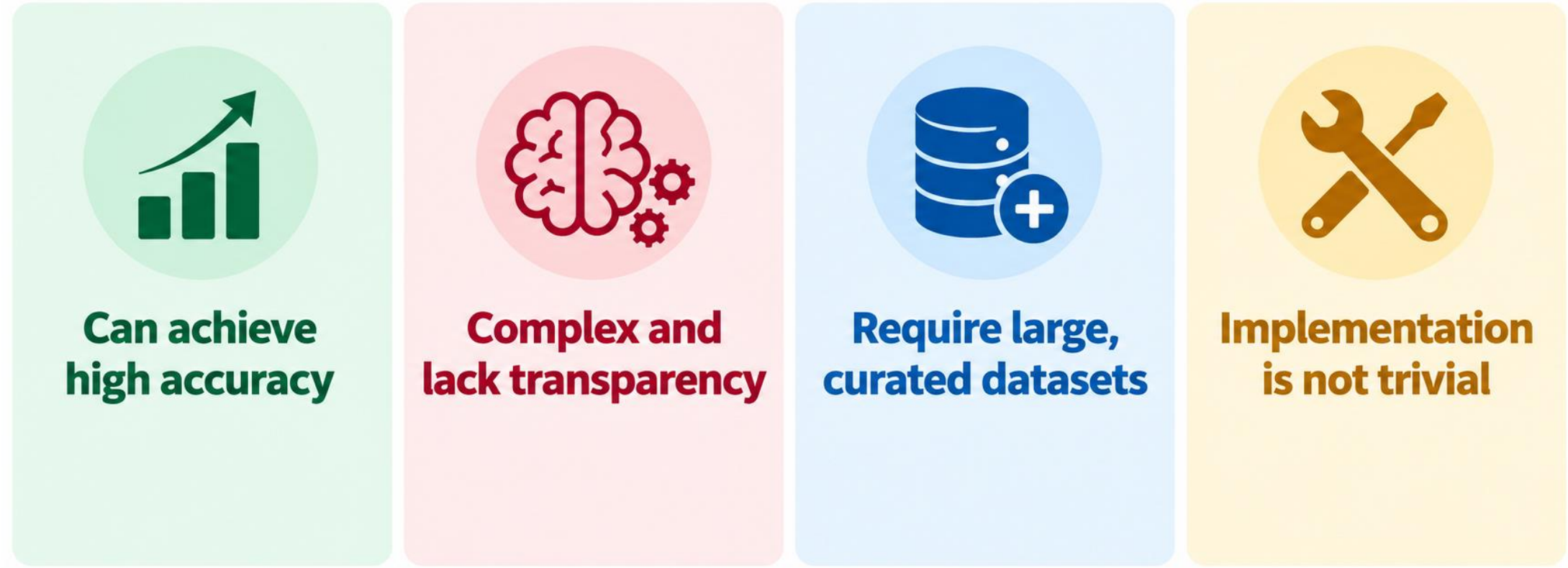


IMAGE GENERATED WITH CHATGPT

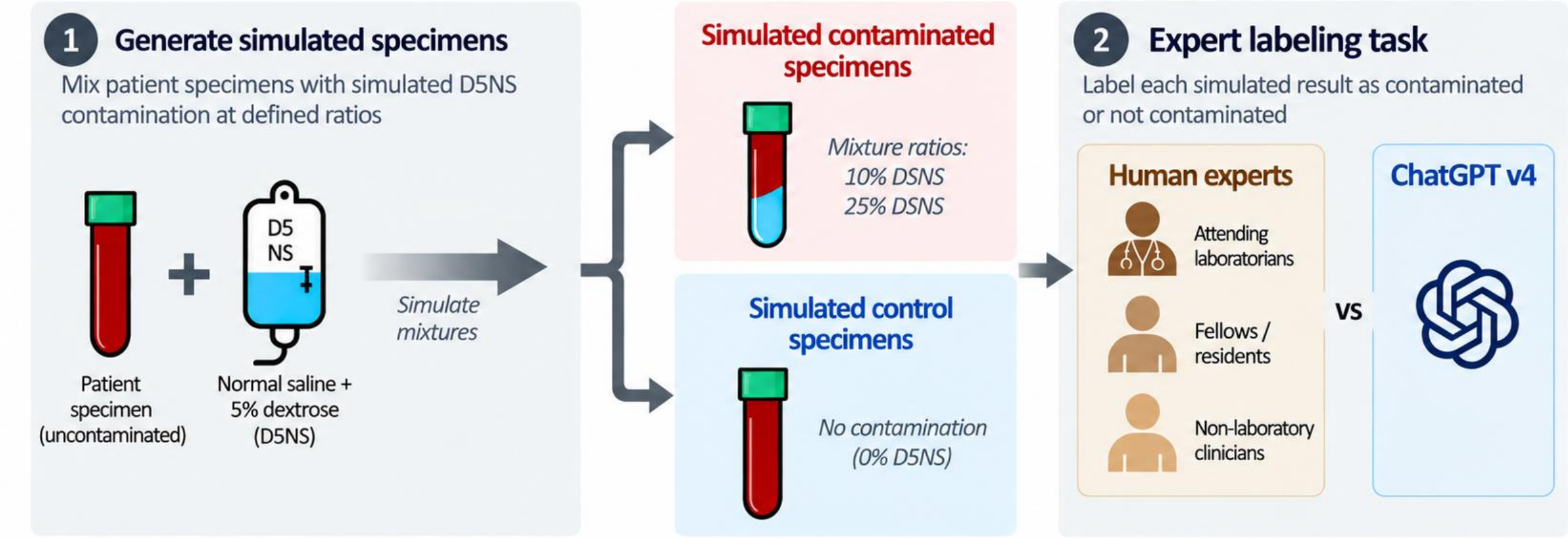
IV Fluid Contamination as a Target for LLM Application



Nick Spies, MD

> *What about a **foundation large language model (LLM)**?*

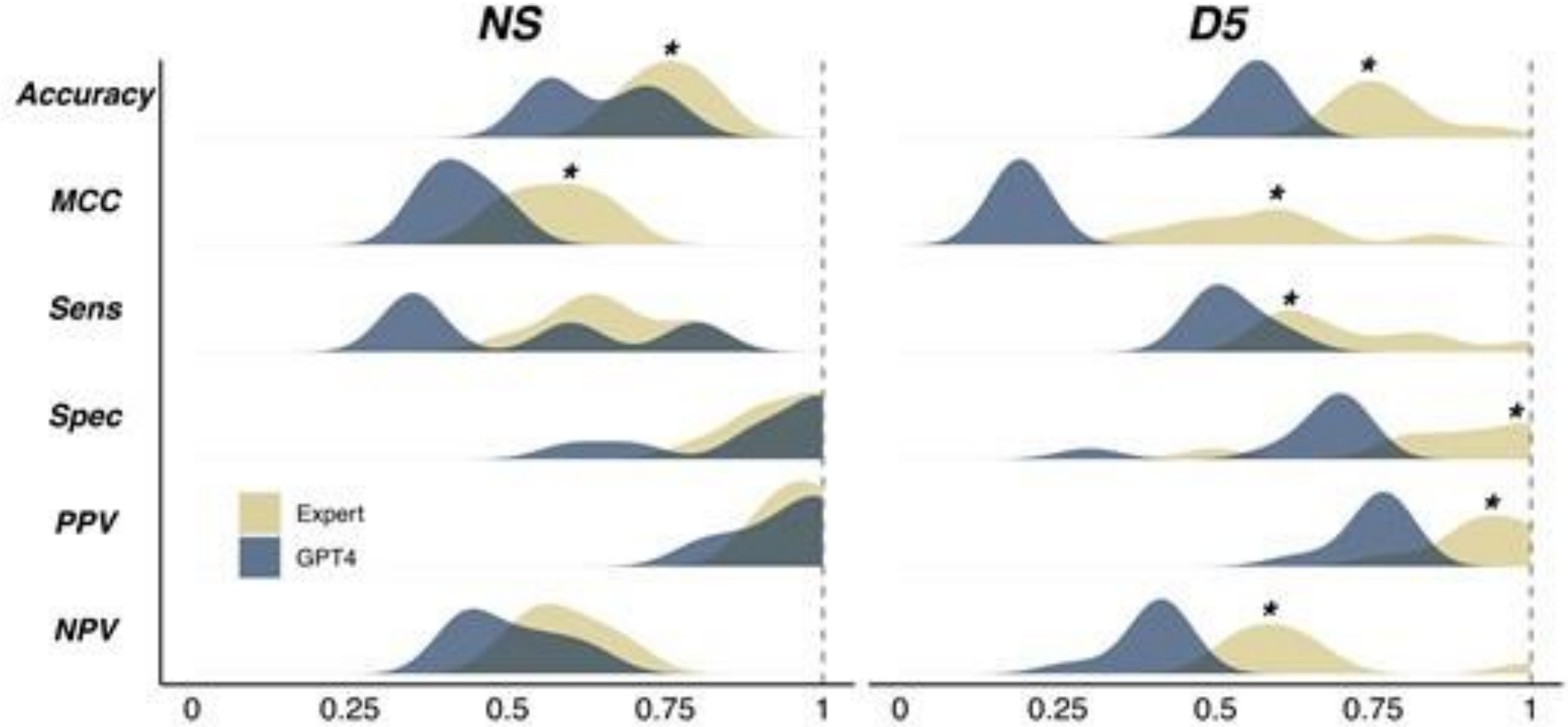
Study Design



Spies 2023 JALM PMID: 37702018

IMAGE GENERATED WITH CHATGPT

ChatGPT Underperformed Human Experts



Gold standard: simulated IV fluid detection

Traditional ML Versus Foundation Models

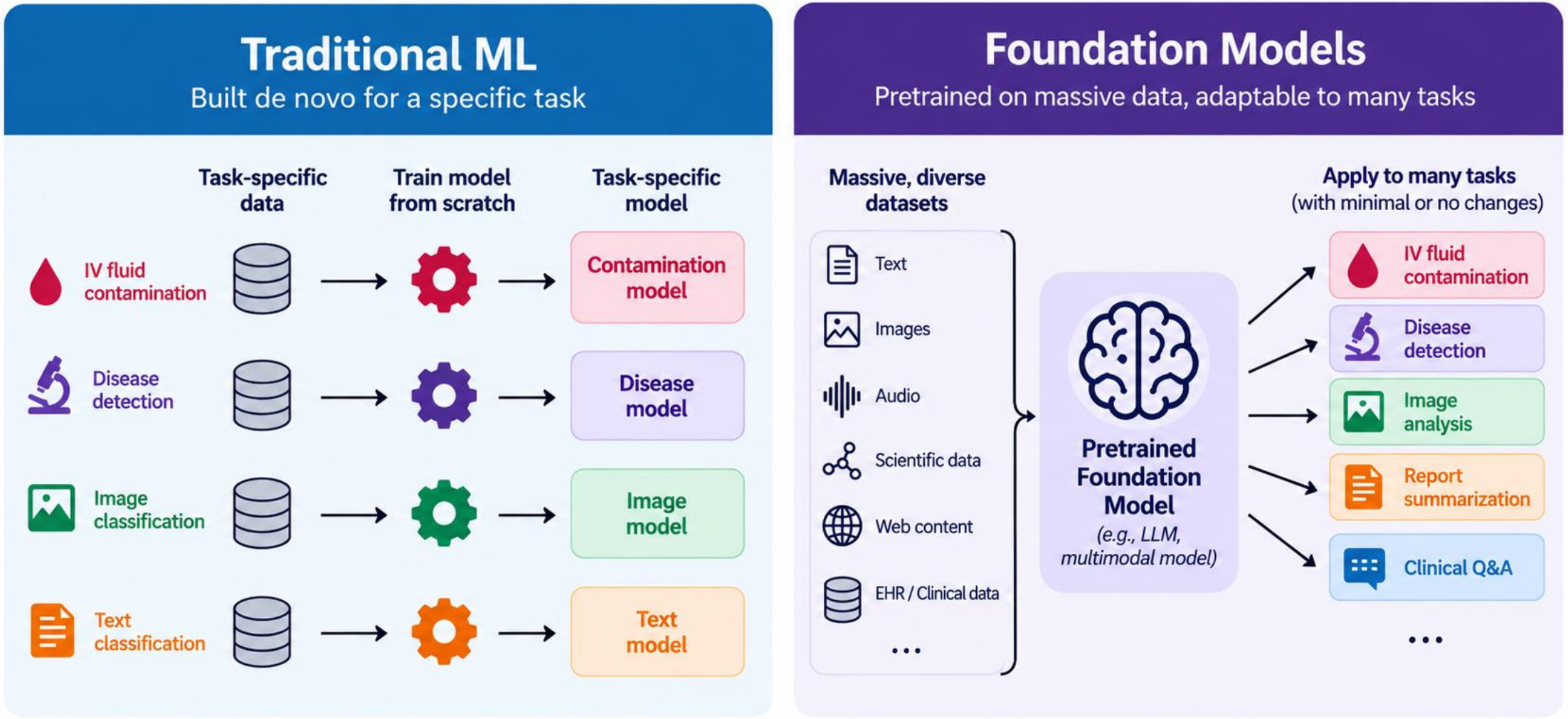


IMAGE GENERATED WITH CHATGPT

Foundation Models/LLMs for IV Fluid Contamination



IMAGE GENERATED WITH CHATGPT

Summary of IV Fluid Contamination Case Study

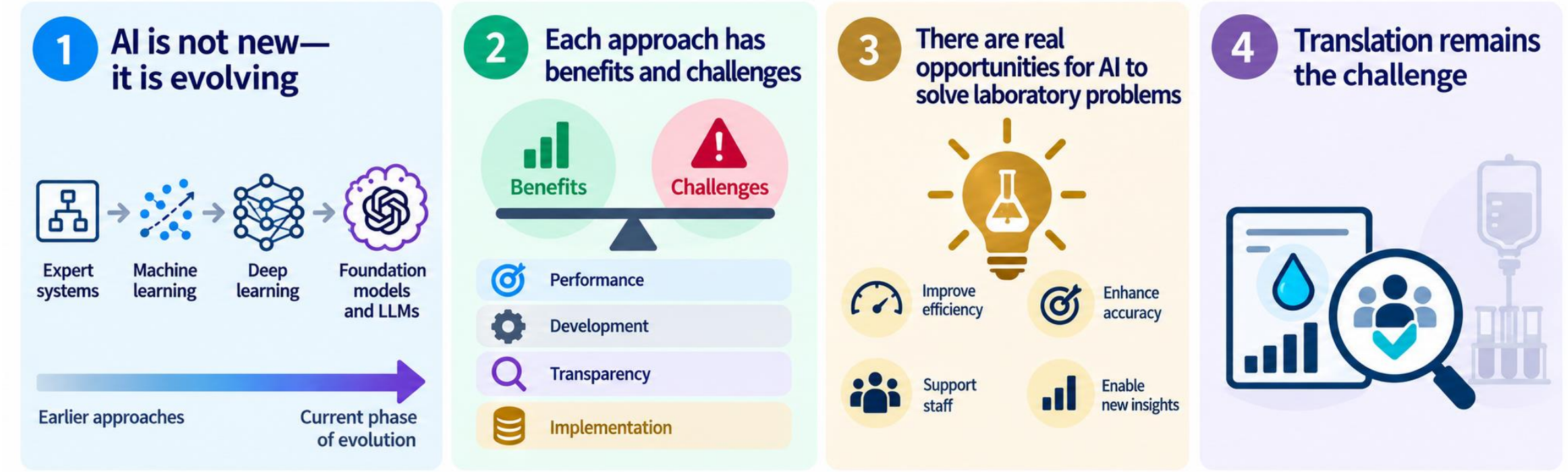


IMAGE GENERATED WITH CHATGPT

Challenges To AI Implementation In The Laboratory

- Risk aversion
- Lack of familiarity
- Limited infrastructure
- Insufficient validation
- Lack of standards and guidelines
- Regulatory ambiguity
- Uncertain reimbursement



Barriers to implementation

Why Laboratory Medicine Deserves a Seat at the Table

- Long history of responsible healthcare technology deployment
- Experts in data-generating processes
- Central hub in healthcare
- Access to rich data assets



CONCLUSIONS

- Laboratory Medicine is fertile ground for the development and deployment of AI applications to improve patient care and human health
- There remain many barriers to optimally implementing AI in laboratory practice
- Laboratory Medicine is a valuable partner in the responsible application of healthcare AI

Acknowledgements

ARUP Laboratories



Nicholas Spies, MD

Yale University



Thomas Durant, MD



Joe El-Khoury, PhD

University of Rochester



Leah Militello, MD, MBA

Washington University School of Medicine

Section of Clinical Chemistry



Christopher Farnsworth, PhD

Kaise Permanente



Vahid Azimi, MD


WashU Medicine