



AI and Food Allergy: New Tools, Opportunities & Challenges

Nicholas L. Rider, DO

Professor, Department of Health Systems & Implementation Science

Section of Allergy-Immunology

Virginia Tech Carilion School of Medicine & The Carilion Clinic

EFACC

West Palm Beach, FL

9 January 2026

Outline

- **AI in Healthcare:** History, Opportunities and Challenges
- **AI in A&I:** Opportunities Abound
- **The Diagnostic Lag:** Application of AI
- **A Framework for Tool Selection:** What's the Need?
- **Key Takeaways**

Learning Objectives:

Upon completion of this learning activity, participants should be able to:

- Describe the current benefits and limitations of AI in healthcare.
- Articulate a strategy for AI tool selection as applied to food allergy use cases.
- Define a presently successful use case of AI implementation in clinical immunology.

Current State: AI Epochs

1.0: "Classic ML"

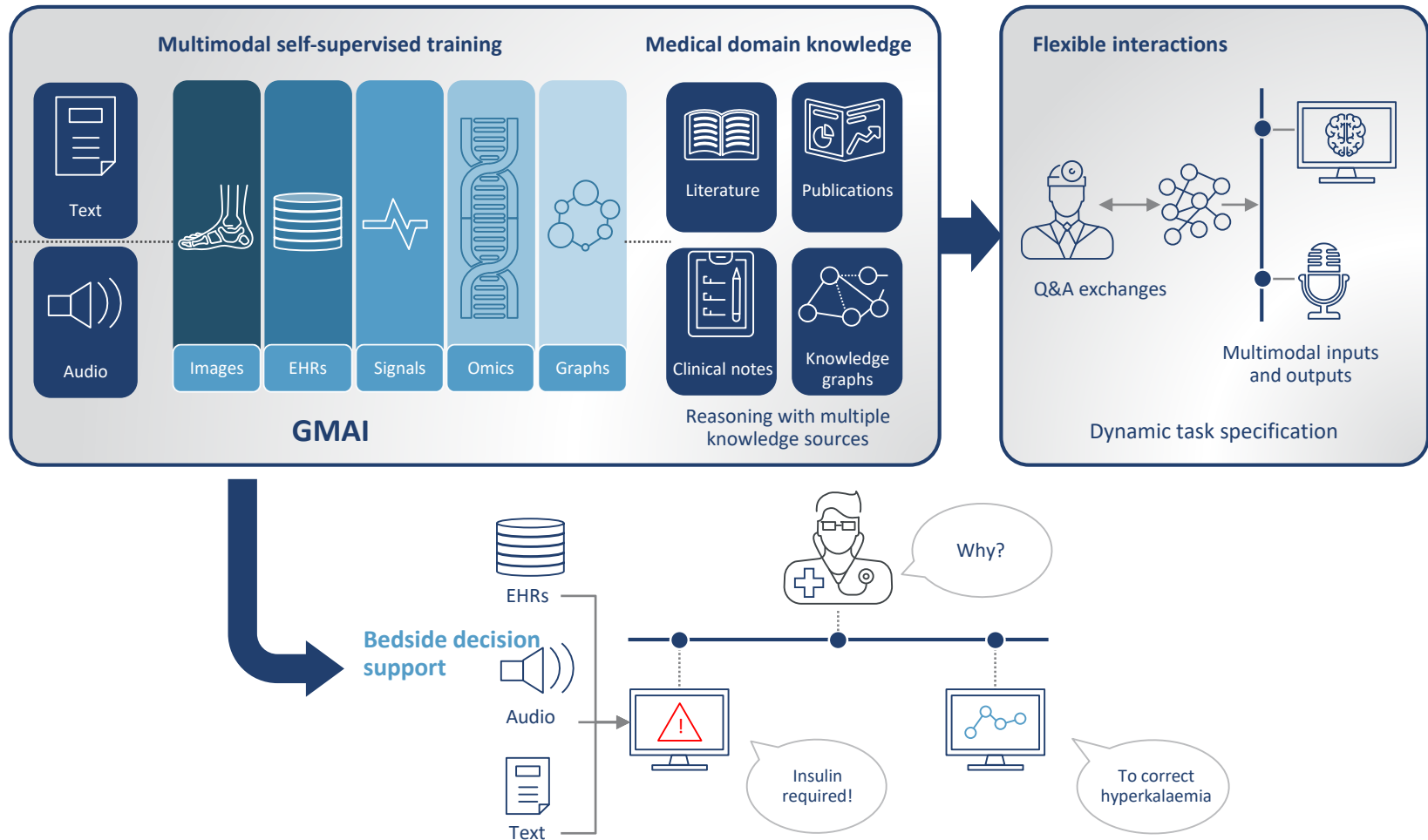
2.0: Deep Learning

3.0: LLMs

Figure. Artificial Intelligence (AI) 1.0, 2.0, and 3.0

Approximate beginning year	1950s	2011	2018-2022
	AI 1.0 Symbolic AI and probabilistic models	AI 2.0 Deep learning	AI 3.0 Foundation models
Core functionality and key features	Follows directly encoded rules (if-then rules or decision trees)	Predicts and/or classifies information Task-specific (1 task at a time); requires new data and retraining to perform new tasks	Generates new content (text, sound, images) Performs different types of tasks without new data or retraining; prompt creates new model behaviors
Training method	Rules based on expert knowledge are hand-encoded in traditional programming	Learning patterns based on examples labeled as ground truth	Self-supervised learning from large datasets to predict the next word or sentence in a sequence
Performance capabilities	Follows decision path encoded in its rules. <i>Eg, ask a series of questions to determine whether a picture is a cat or a dog.</i>	Classifies information based on training: <i>"Is this a cat or a dog?"</i> <i>"How many dogs will be in the park at noon?"</i>	Interprets and responds to complex questions: <i>"Explain the difference between a cat and a dog."</i>
Examples of performance	IBM's Deep Blue beat the world champion in chess Health care: Rule-based clinical decision support tools	Photo searching without manual tagging, voice recognition, language translation Health care: diabetic retinopathy detection, breast cancer and lung cancer screening, skin condition classification, predictions based on electronic health records	Writing assistants in word processors, software coding assistants, chatbots Health care: Med-PaLM and Med-PaLM-2, medically tuned large language models, PubMedGPT, BioGPT
Examples of challenges and risks	Human logic errors and bias in encoded rules lead to limited capability with real-world situations	Out-of-distribution problems (real-time data differs from training data) Catastrophic forgetting (not remembering early parts of a long sequence of text) Bias related to underlying training data	Hallucinations (plausible but incorrect responses based solely on predictions) Grounding and attribution Bias related to underlying training data and semantics of language in datasets

LLMs: Healthcare AI



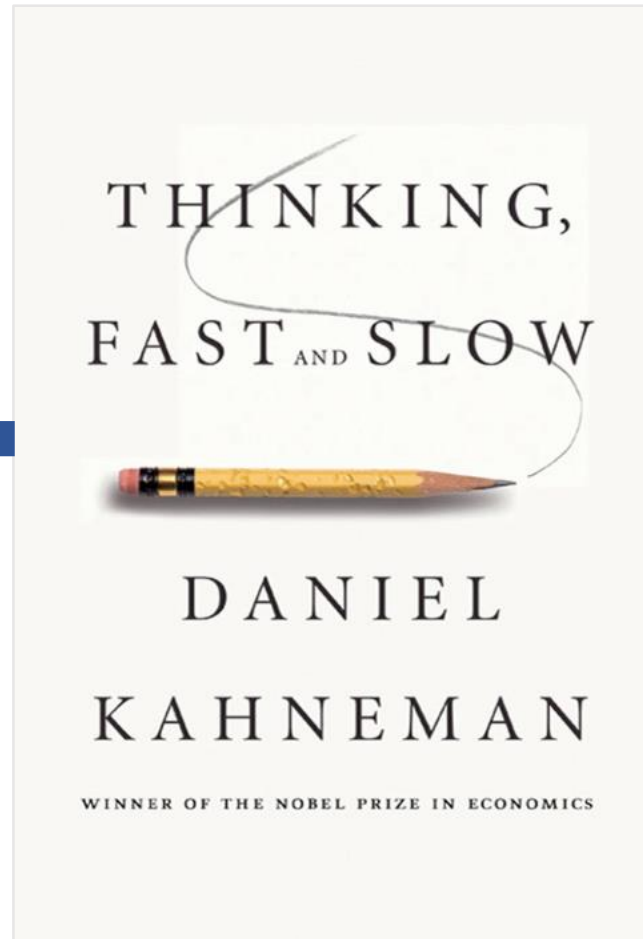
AI: Artificial Intelligence; ML: Machine Learning; LLM-Large Language Model

Adapted from Moor et al. *Nature* 616, 259–265 (2023)

What is AI Actually Capable of Today?

System 1

- Fast
- Subconscious
- Automatic
- Error Prone



System 2

- Slow
- Conscious
- Effortful
- Complex Decision
- Reliable

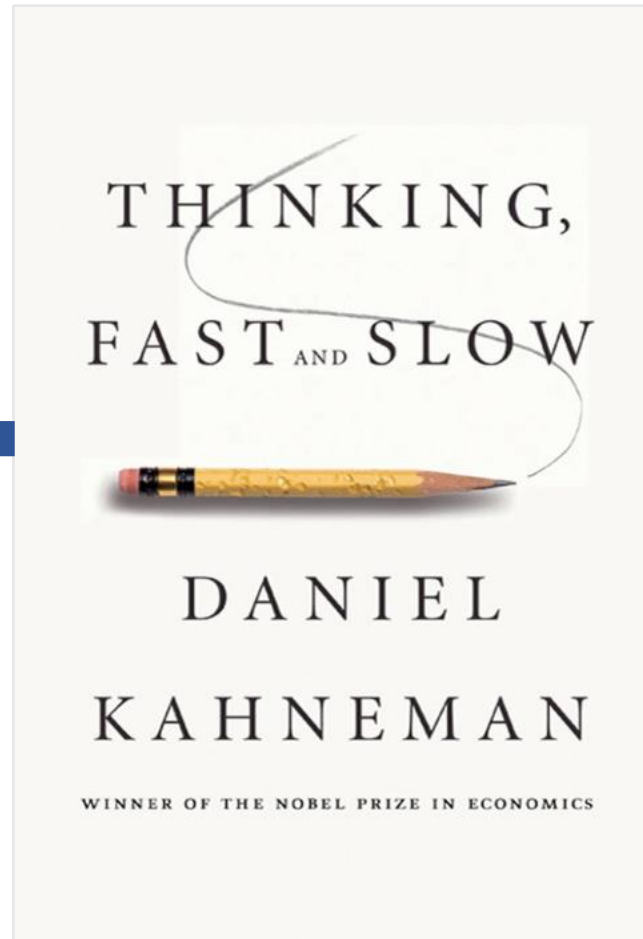


What is AI Actually Capable of Today?

System 1

Recall/Memory

- Humans
- Other Sentient Beings
- AI

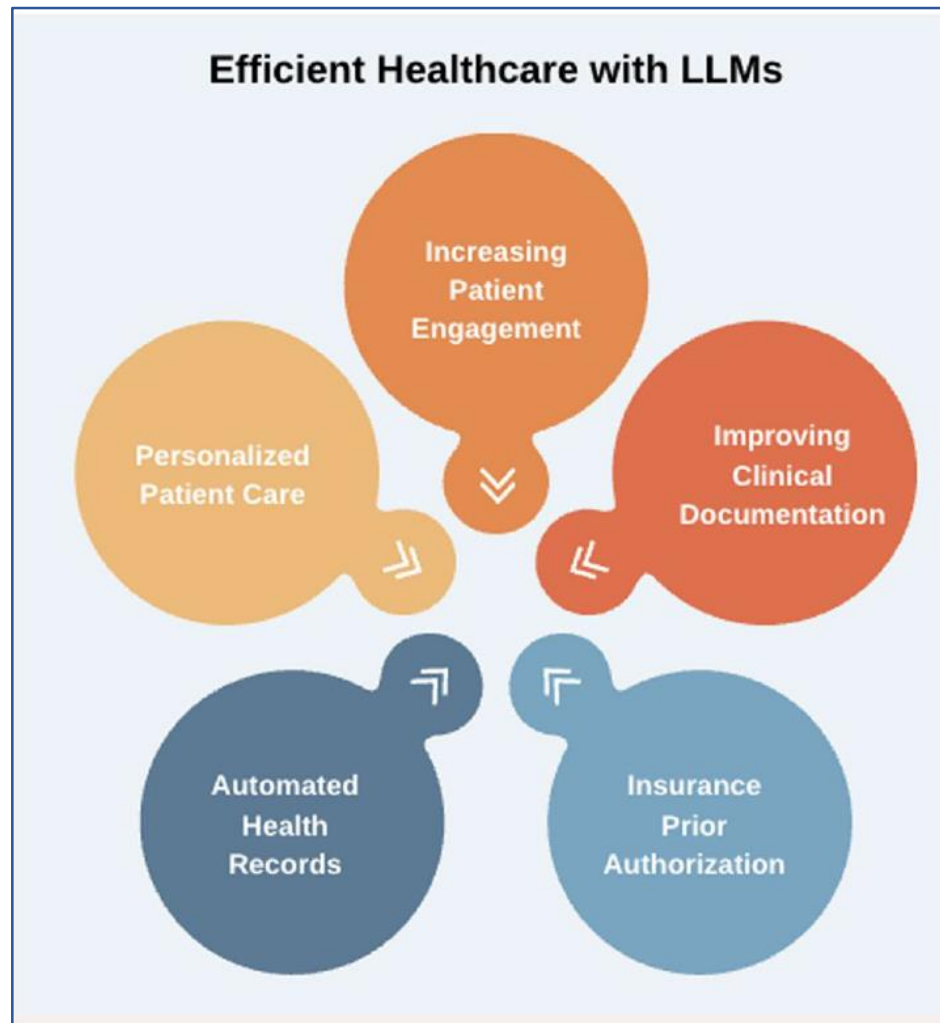


System 2

Reasoning

- Humans
- Other Sentient Beings

Where Is AI Proving Useful?



Tripathi S. et al. JAMIA 2024, 31(6)

AI in Healthcare: Opportunities

Q: What Do We ALL Want From Healthcare?

A: Lots of things, but essentially.....

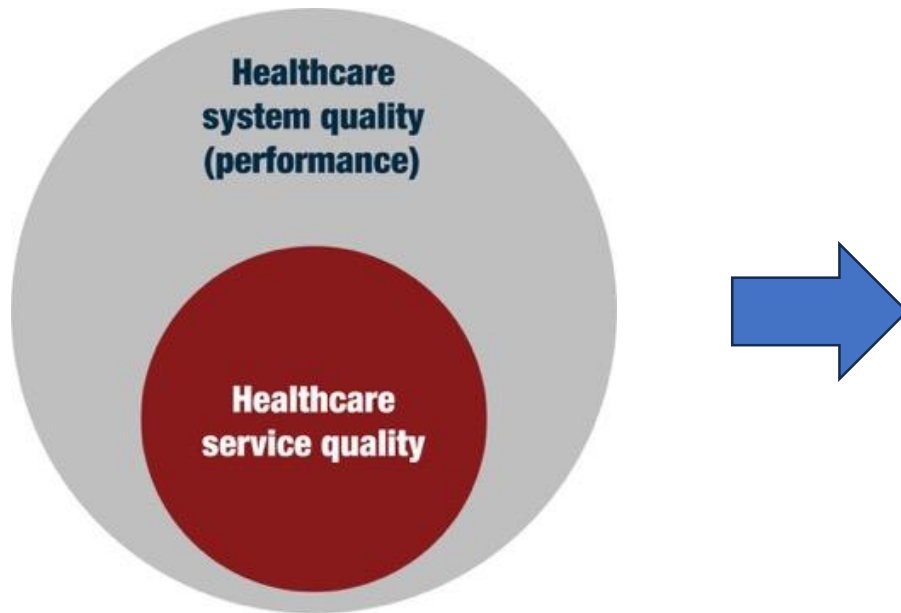


www.chatgpt.com

$$\text{Value} = \frac{\text{Quality}}{\text{Cost}}$$

Lots to Unpack

AI in Healthcare: Can AI Bring Value?

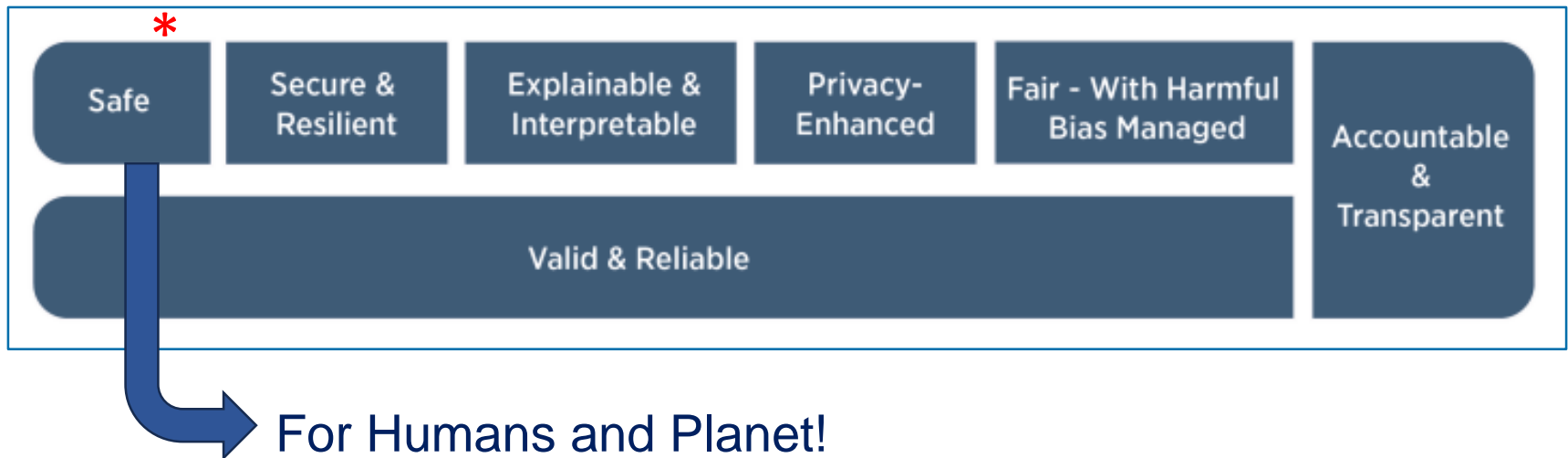


Busse R, Panteli D, Quentin W. Imp. Hlth. Qual. In Eur. 2019



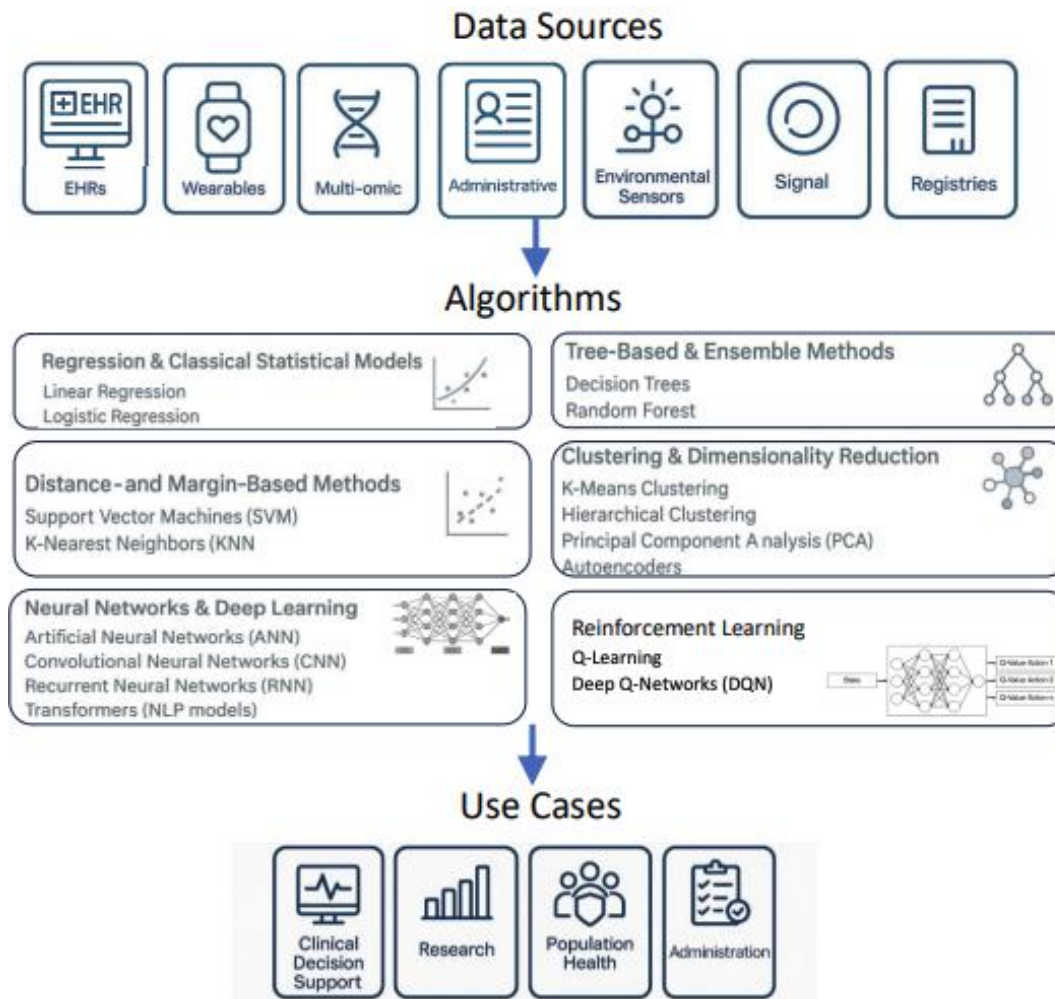
<https://permanente.org/medical-excellence/what-is-quality-healthcare-and-why-it-matters/>

AI in Healthcare: Can We Mitigate AI Risk?

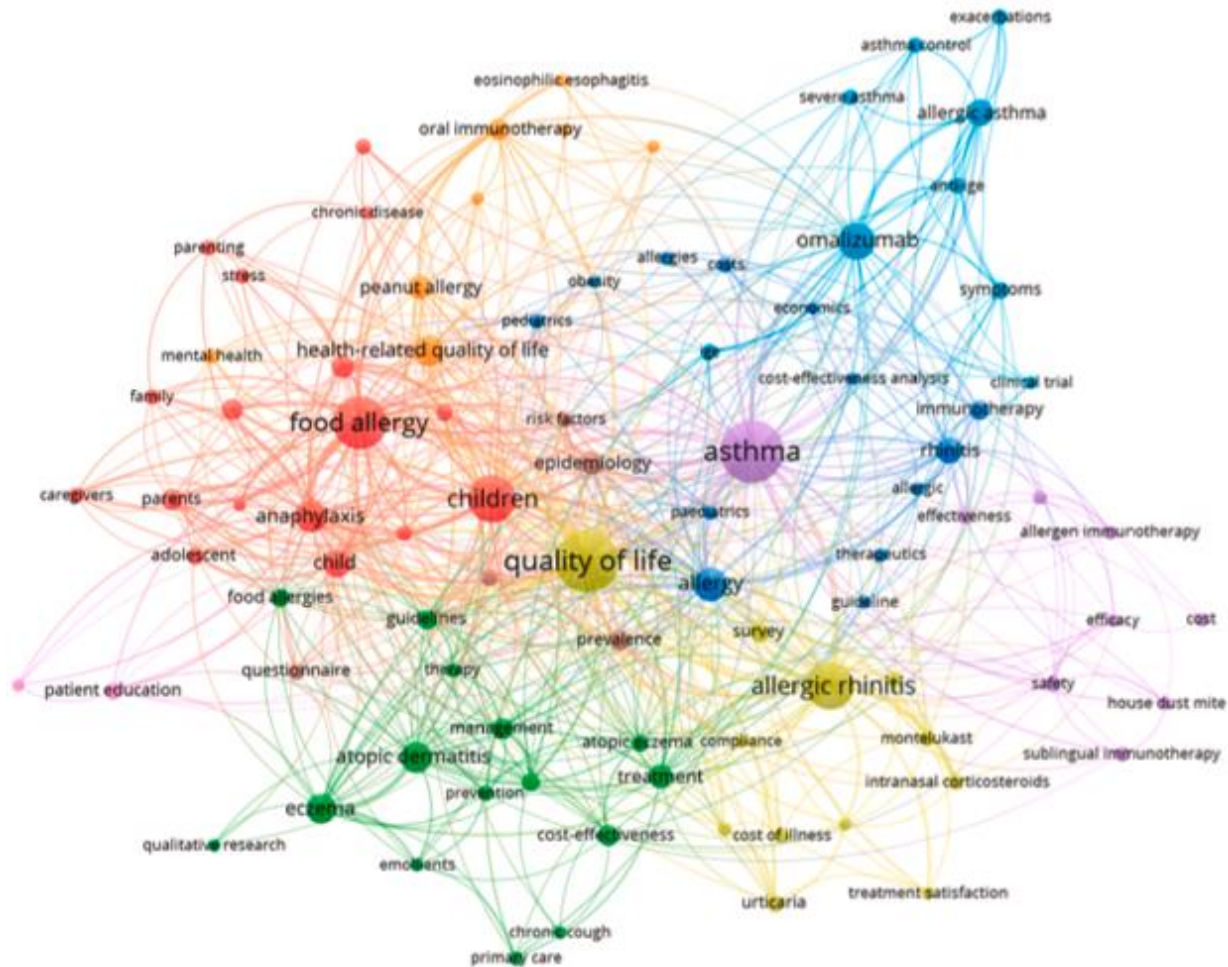


AI RMF 1.0 NIST AI 100-1
<https://nvlpubs.nist.gov/nistpubs/ai/NIST.AI.100-1.pdf>

AI in A&I: Multiple Opportunities Exist



AI in A&I: Multiple Opportunities Exist



Goktas P et al. JACI Global Aug 2025

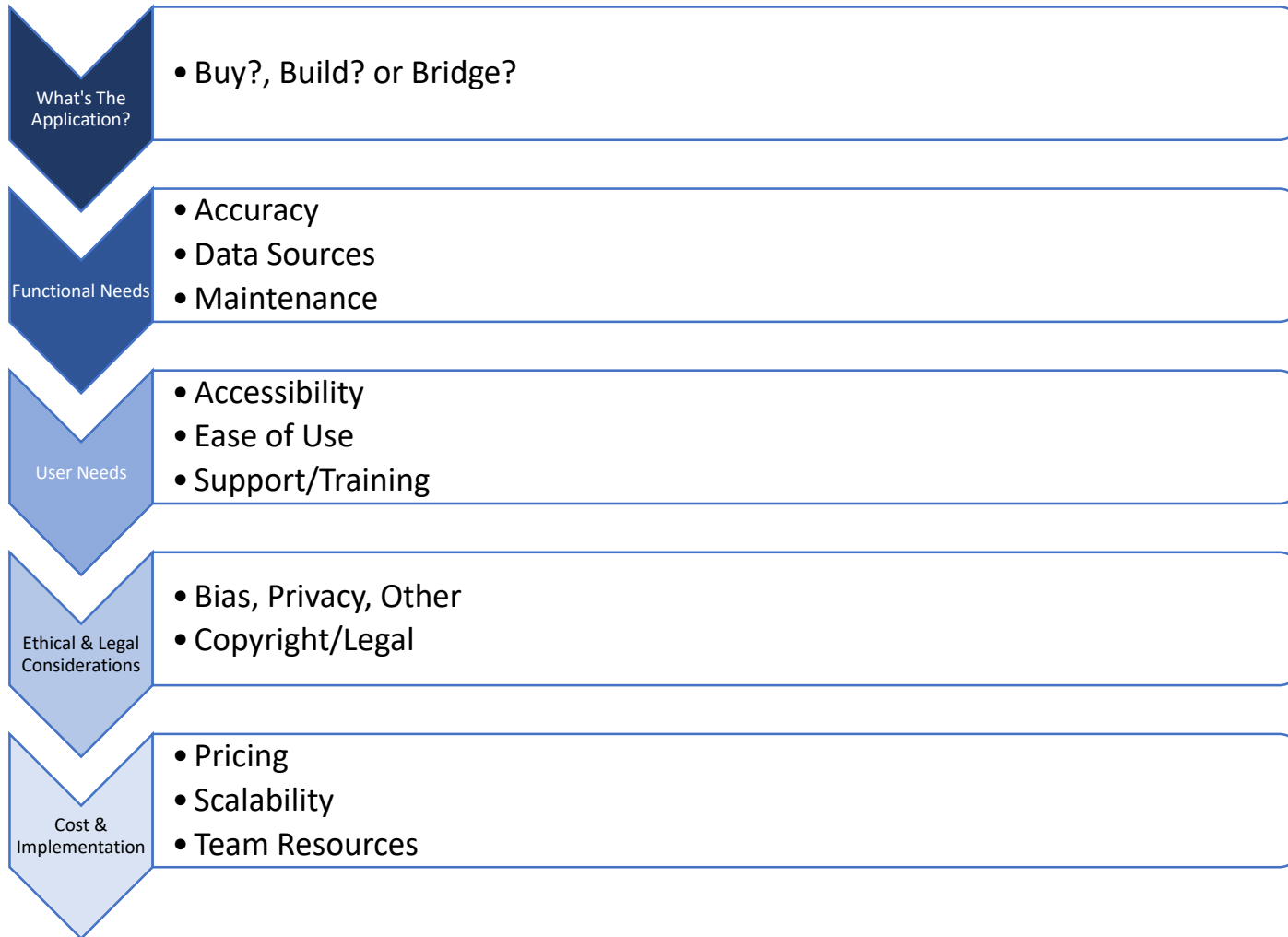
AI for Food Allergy: Evaluating Tools



A Framework: Fishing vs. Listing



A Framework: AI Use for Food Allergy



A Framework: AI Use for Food Allergy

- What is Your Question/Task?
- Is There A Solution Already?

What's The Application?

- Buy?, Build? or Bridge?

Example:

Paradigms and perspectives

Can artificial intelligence (AI) replace oral food challenge?



Sindy K. Y. Tang, PhD,^a Nicolas Castaño, MS,^a Kari C. Nadeau, MD, PhD, FAACAAI,^{a,b} and Stephen J. Galli, MD^{a,c,d} *Stanford, Calif, and Boston, Mass*

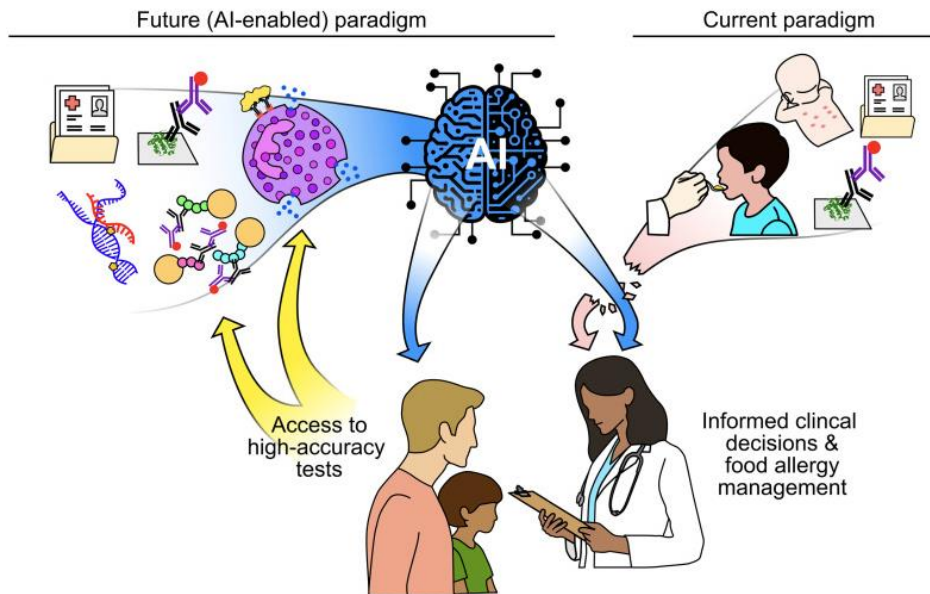
JACI v.153, n.3, 2024

A Framework: AI Use for Food Allergy

- What is Your Question/Task?
- Is There A Solution Already?

What's The Application?

- Buy?, Build? or Bridge?



A Framework: AI Use for Food Allergy

- **Do You Value Sensitivity or Specificity?**
- **Is Training Data Available?**



Functional
Needs

- Accuracy
- Data Sources
- Maintenance

- Sensitivity – True Positive Rate = $TP / (TP + FN)$
- Tell Me About Your Data:
 - What are its strengths/limitations?
 - Can your training data effectively model question of interest?
 - Data Quality?
 - Generalizability?
- How to Sustain Model?

A Framework: AI Use for Food Allergy

- **How Will Users Interact?**
- **Are They Ready?**



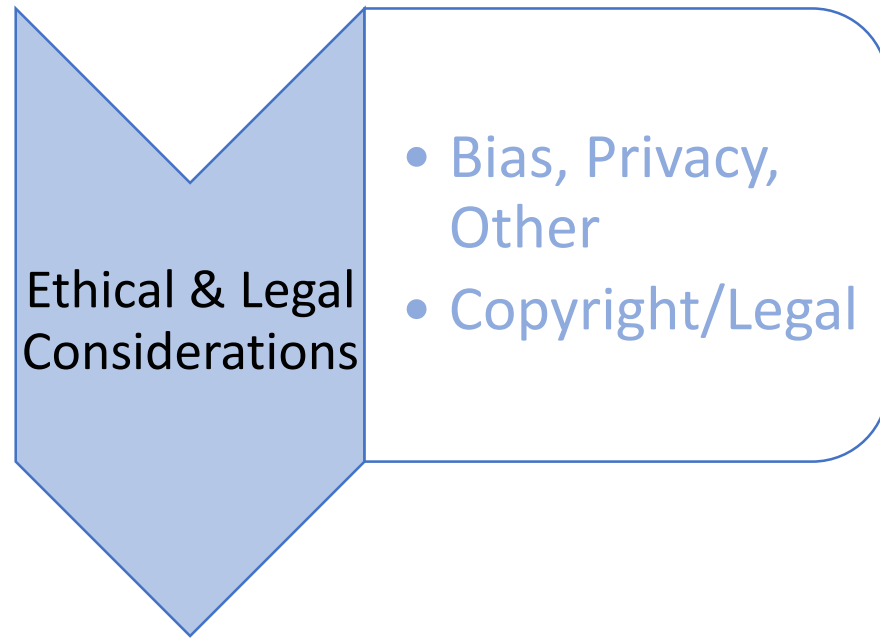
User
Needs

- Accessibility
- Ease of Use
- Support/Training

- What format should predictions be delivered?
- How trustworthy and interpretable are predictions?
- Do you want a user interface?
 - Human factors elements?
- Can't just “turn on” a model, need to train users...

A Framework: AI Use for Food Allergy

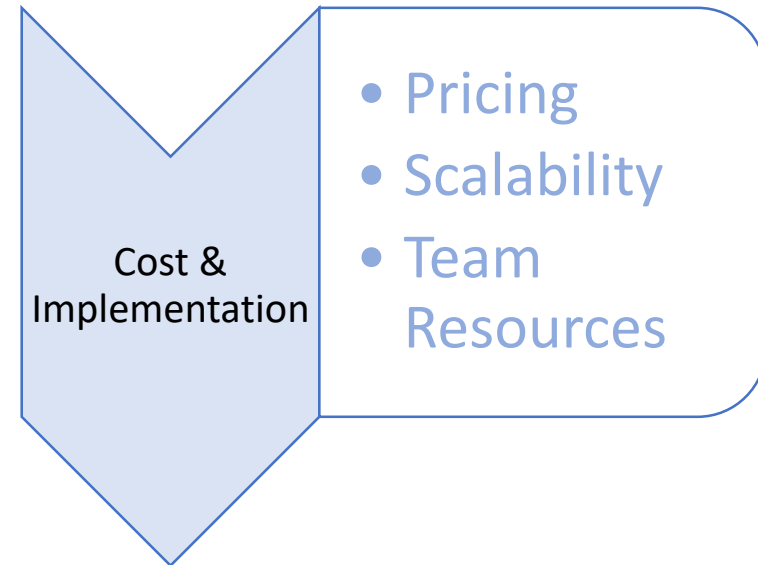
- **What are the Limitations?**
- **IP Considerations?**



- No single AI model will serve everyone, who are you missing, where does the model fail?
- Back to Buy or Build – what are your guardrails for:
 - Maintaining IP
 - Adhering to use agreements/updates, etc.

A Framework: AI Use for Food Allergy

- **What's Your Budget?**
- **Can Local Teams Support?**



- What is your budget for standing up AI, maintaining AI?
- Do you have local AI expertise, IT, Analytics, etc?
- Will you need an ongoing relationship with an AI vendor?

The Learning Health System (LHS): Conceptual Definition

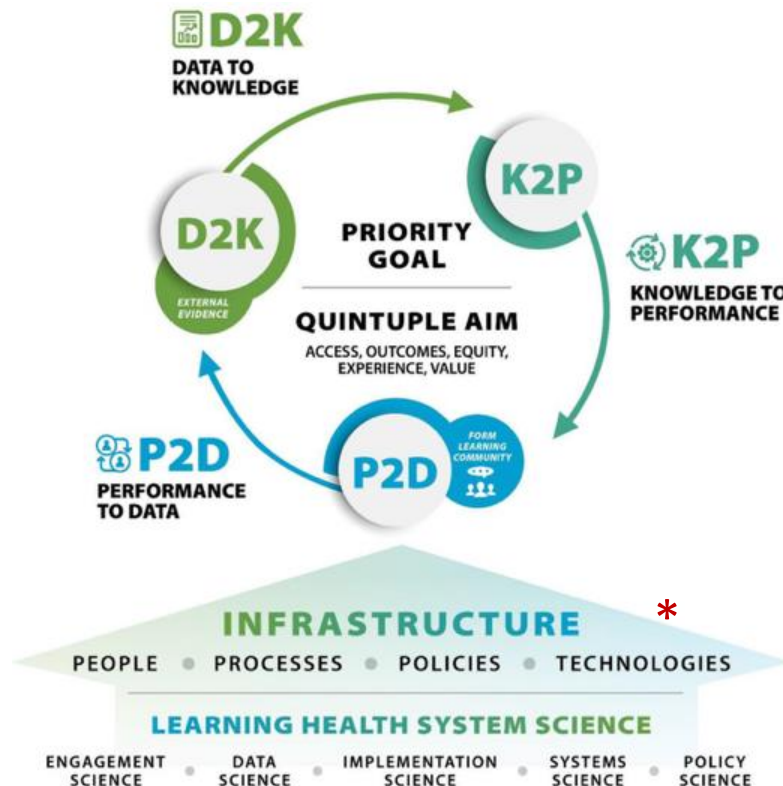
“...a learning health system — in which science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the delivery process and new knowledge captured as an integral by-product of the delivery experience...?”



NATIONAL ACADEMY OF MEDICINE

<https://nam.edu/our-work/programs/leadership-consortium/learning-health-system-series/>

LHS Goal: Improving Care Value

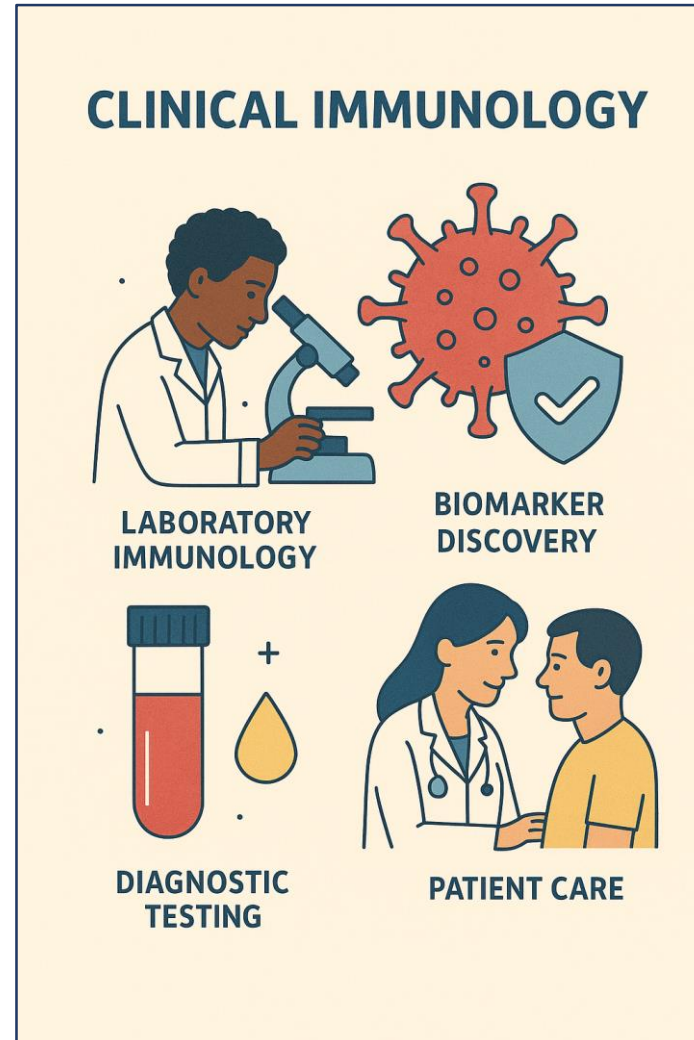


Value =
Quality/Cost

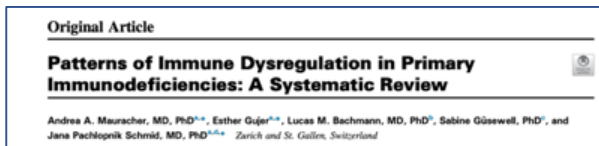
***Where AI Fits**

Kilbourne AM et al Health Serv. Res. 2024

AI in A&I: Clinical Immunology Real-World Example



PI Diagnostic Lag: Clinical Immunology



- **Common Variable Immunodeficiency – Mean TTDx = 8.8yrs(CI: 8.2-9.3) Odoletkova et al. 2018**
- **Immune Dysregulatory Disease – Median TTDx = 5yrs(IQR 1-14) Staus et al. 2023**
- **Primary Antibody Deficiencies – Median TTDx = 9.5yrs Messelink et al. 2023**

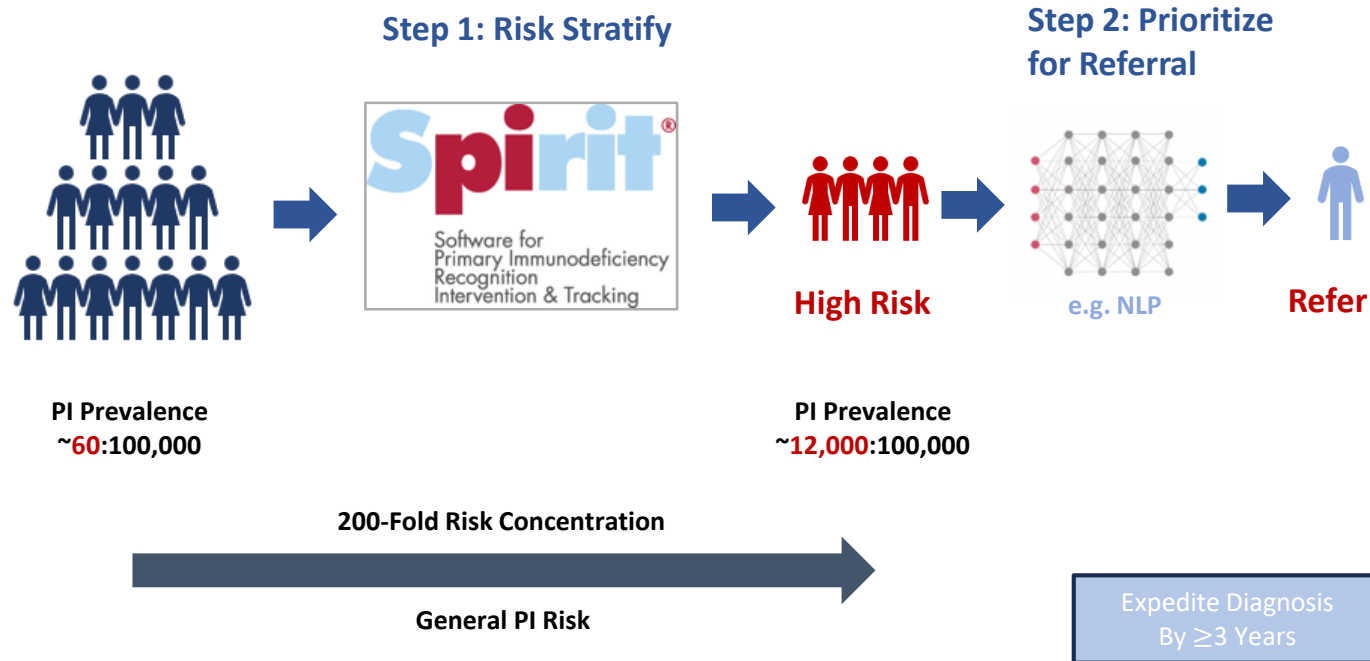


- Long Diagnostic Odysseys
- Suboptimal Outcomes
- Missed Opportunities for Best Care
- Inappropriate Referrals
- Excessive Costs

Branch A et al. Ped. Allg. Immunol. 2021 Nov 32(8)
Mauracher AA et al. JACI Pract. 2021 Feb 9(2)
Isono M et al. PLoS One 2022 Mar 18 17(3)

Odoletkova I et al. Orph. J. Rare Dis. 2018 Nov 12 13(1)
Staus P et al. J. Clin. Immunol. 2023 Aug 43(6)
Messelink M et al. J. Clin. Immunol. 2023 Nov 43(8)

Using AI for Population Level Risk Stratification:



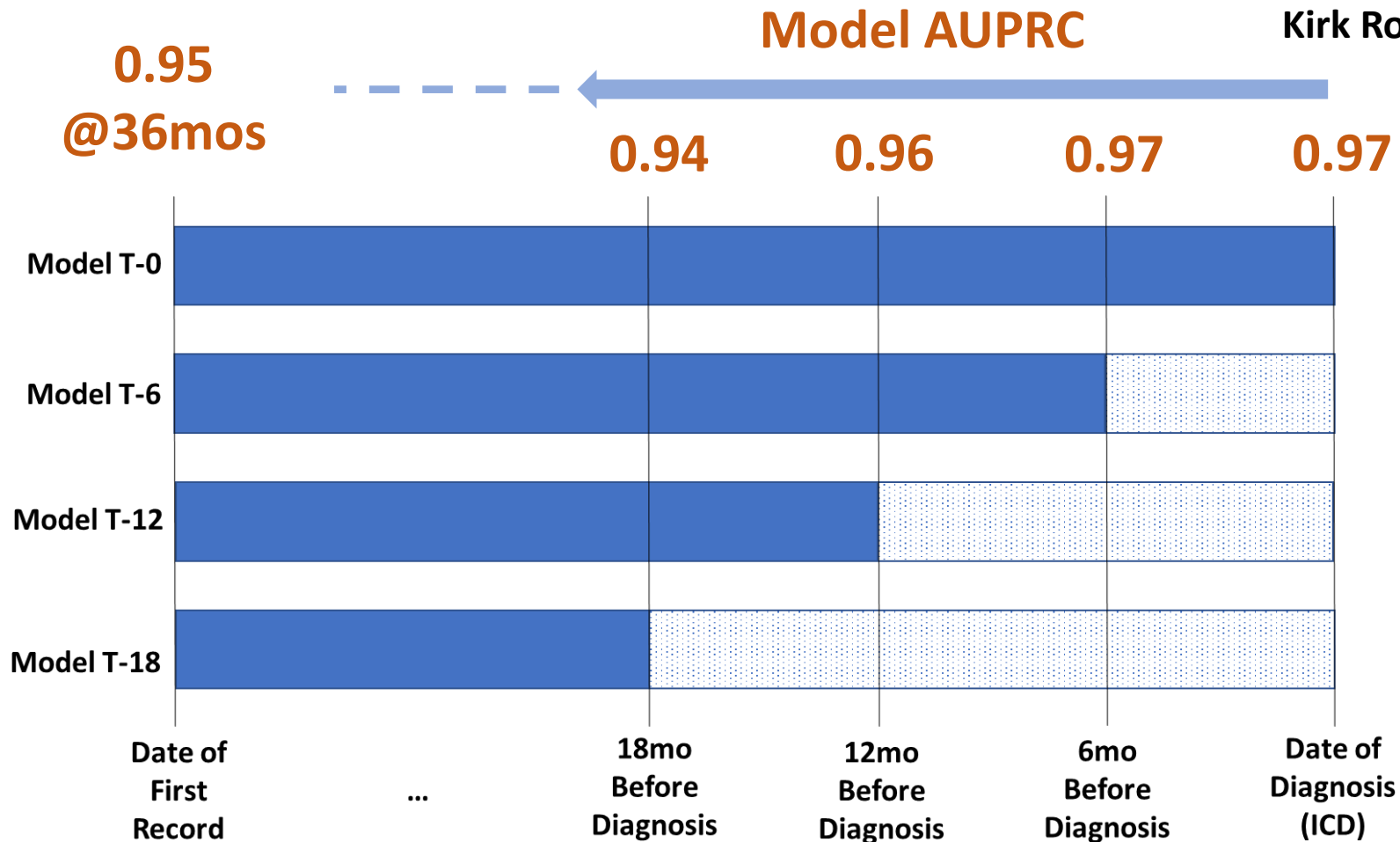
Roberts K et al. JACI Glob 2024 Feb 2; 3(2)
Rider NL et al. JACI 2023 Jan;151(1)

Rider NL et al. JACI 2024 Jun 153(6)

Using AI for Population Level Risk Stratification: AI Performance



Kirk Roberts, PhD

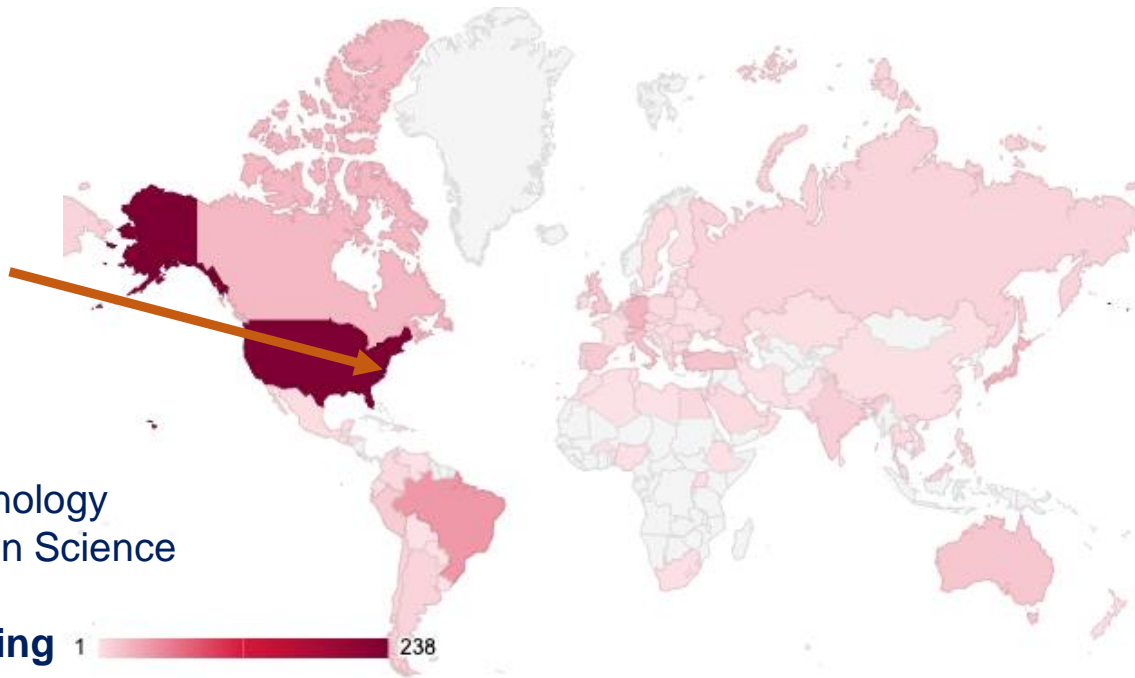


How Do We Get There? Scaling LHS Access Globally



- Informatics
- Data Science
- Clinical Immunology
- Implementation Science
- IT

**Formally Opening
April 2026!!!**



JMCN Expert Density as of October 2024

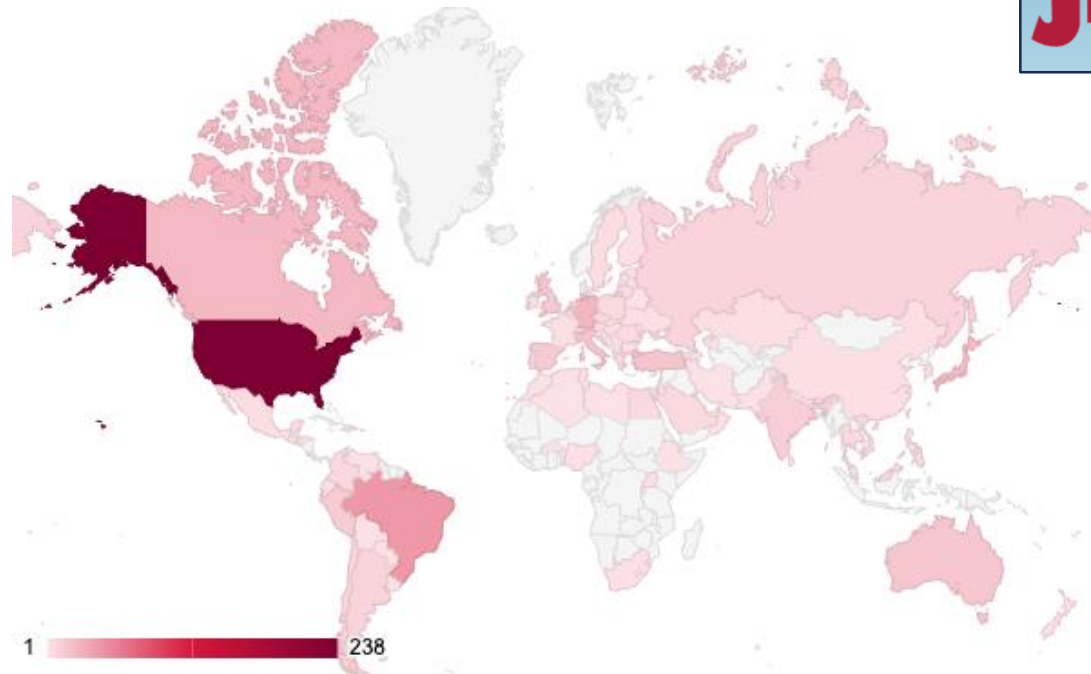
JMCN:

- 930 Experts
- 500 Centers
- 318 Cities
- 89 Countries
- 6 Continents
- Still Growing!

How Do We Get There? Scaling LHS Access Globally



- Implement
- Sustain
- Share Solutions
- Share Best-Practices



JMCN Expert Density as of October 2024

Key Takeaways:

- AI Has and Will Continue to Bring Value for A&I Patient Care, Clinical Operations and Scientific Discovery
- We Need a 'Team of Teams' to Advance AI as a Specialty
- Implementation & Sustainment are Crucial
- Adverse Effects of AI Must Be Understood and Mitigated

Acknowledgements

CHILI Group:

Jacob Blaukovich
Roxanna Farzad, MS
Liangying Liu, MS
Geoffrey Otieno, MS
Tia Parrish
Sarina Nikzad



Kirk Roberts, PhD, MS



Ashok Kurian, MBA (TCH)
Michael Coffey (TCH)
Klaus Loewy (TCH)
Lisa Pompeii, RN, PhD (BCM > CCMC)



Monica Lawrence, MD
Larry Borish, MD



Angela Tyree, RN, BSN



Jordan S. Orange, MD PhD (JMF/CHOP)
Fred Modell (JMF)
Vicki Modell (JMF)
Vanessa Tenenbaum (JMF)
Jessica Quinn (JMF)
Rachel Simoneau (JMF)
Roger Davila (JMF)
Tia Parrish (JMF)



Michael Keller, MD
Alexandra Martinson, MD
Hiroki Morizono, PhD
Anita Patel, MD
Nishad Kulkarni, PhD
Syed Muhammad Anwar, PhD



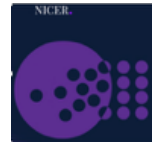
Aaron Chin, MD
Manish Butte, MD PhD



Mei-Sing Ong, PhD
Gurgana Savova, PhD
Yingya Li, PhD



Jocelyn Farmer, MD PhD



Kelly Walkovich, MD
James Connelly, MD
Evelyn Argirokastritis

International Collaborators:

Jacques Riviere, MD
Pere Soler-Palacin, MD, PhD
Cecilia Poli, MD PhD
Silvia Sanchez-Ramon, MD PhD

Funding Agencies:



Thank You!
nick70@vt.edu

