

A decorative graphic on the left side of the slide consists of numerous circles of varying sizes in three colors: dark blue, orange, and white. These circles are scattered across the left half of the slide, with a higher concentration in the center-left area.

Benefits and
Challenges in AI for
Primary Care:

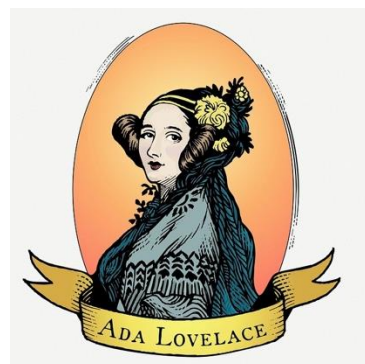
Real World Impact &
Ongoing Monitoring

Jaky Kueper, PhD

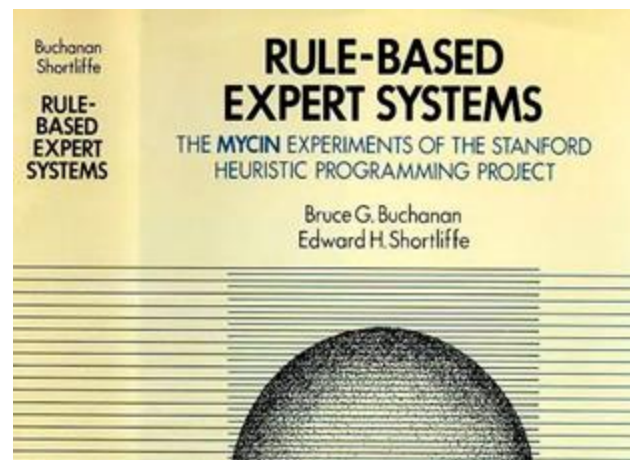
Scripps Research Digital Trials Center

NAPCRG

A *brief* history of milestones in AI methods



1840s
First Computer Algorithm

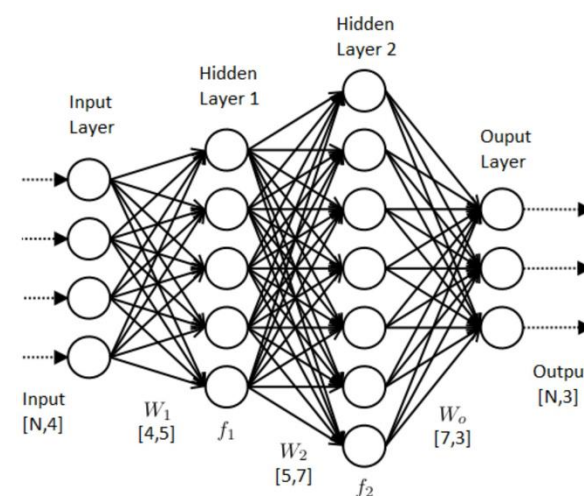


1970s
Rule-Centric Methods
First medical application

1950s
Field of AI Formalized

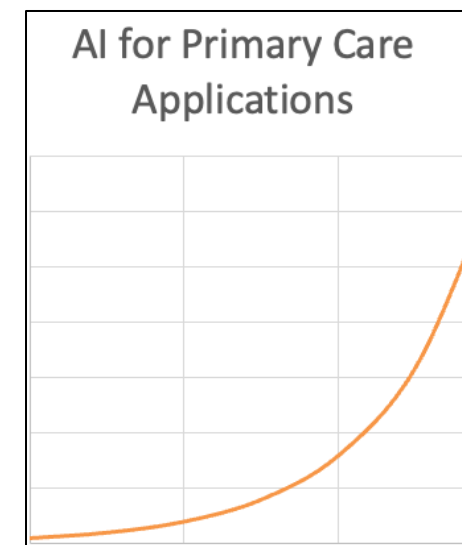


2010s
Data-Centric Methods
Deep learning boom



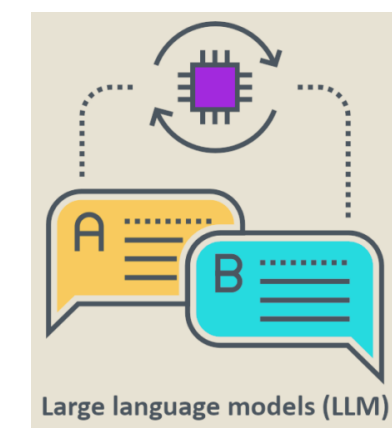
2020s
Narrow AI/ML showing success
at health-relevant tasks

“predicting”
“describing”
“recommending”



Large Language Models and
Generative AI methods

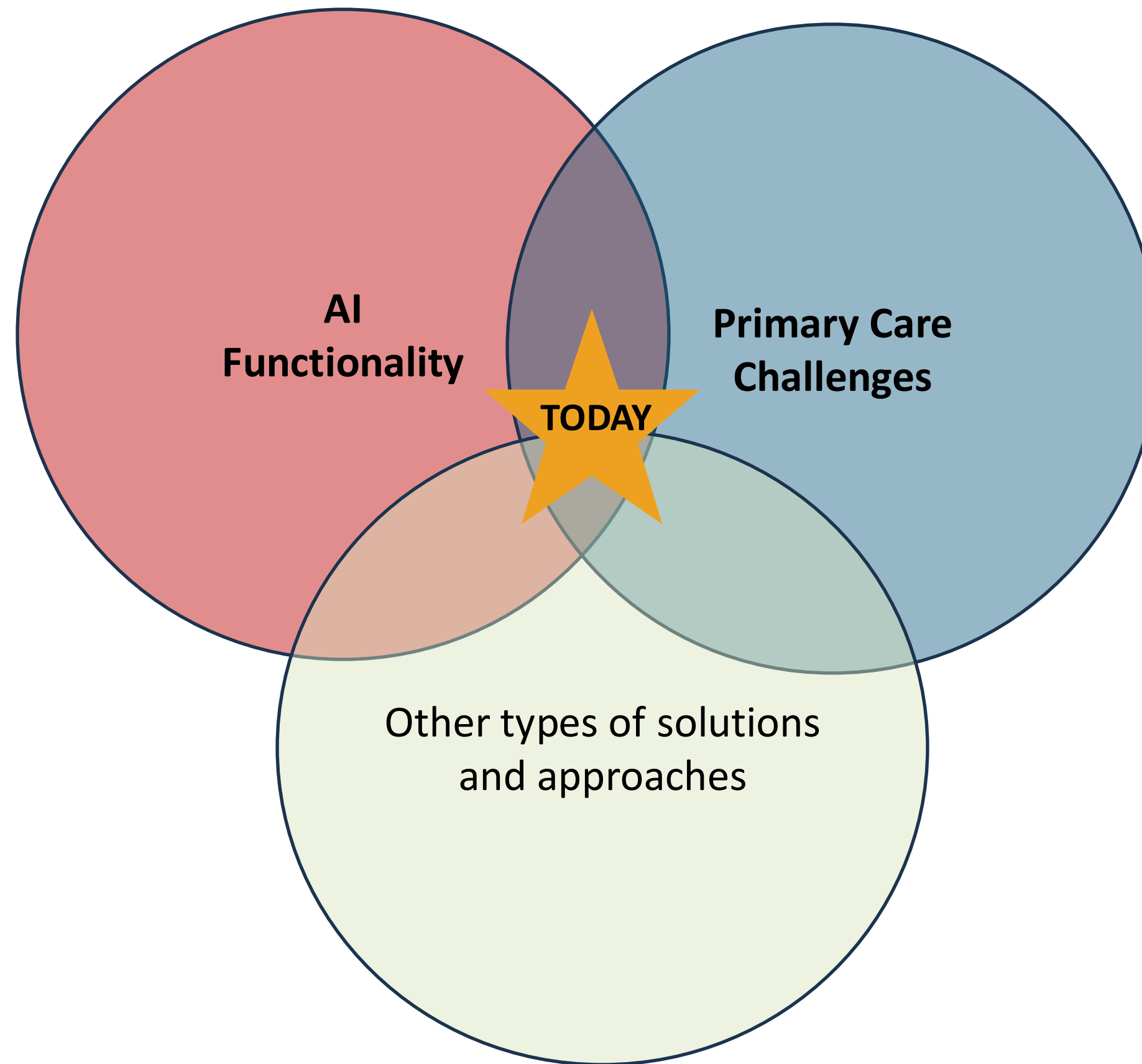
“creating”



Agentic AI methods

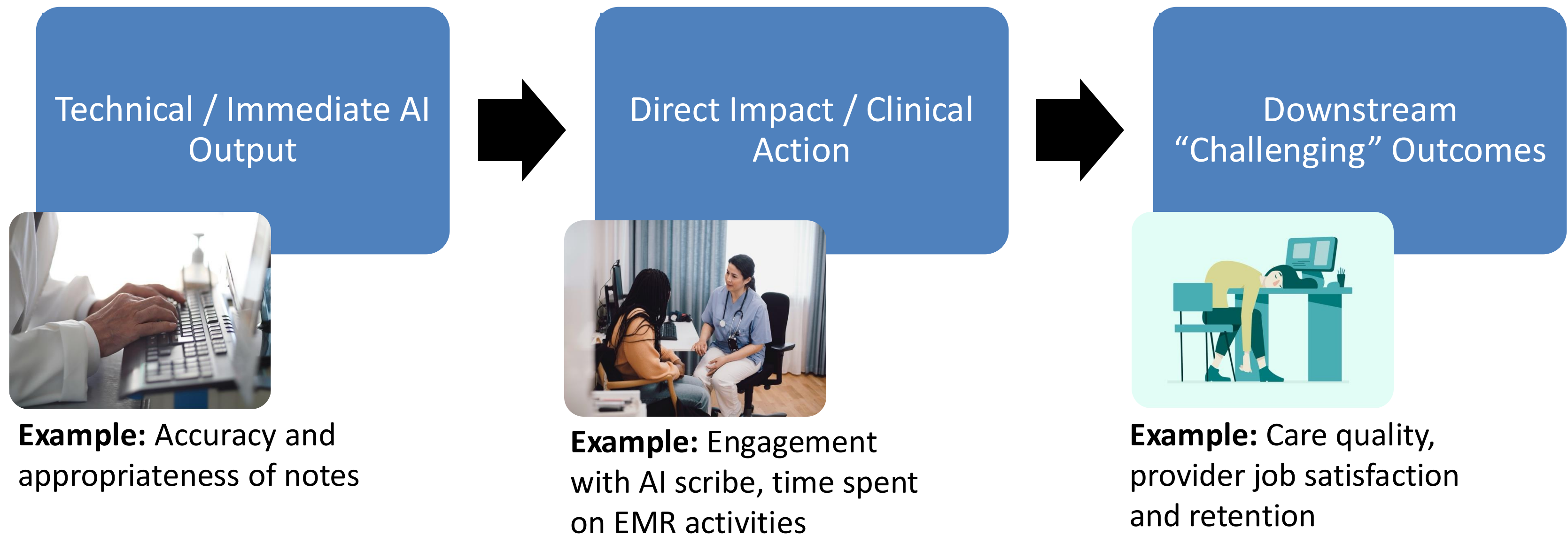
“doing”

Today: AI methods can now address meaningful primary care challenges



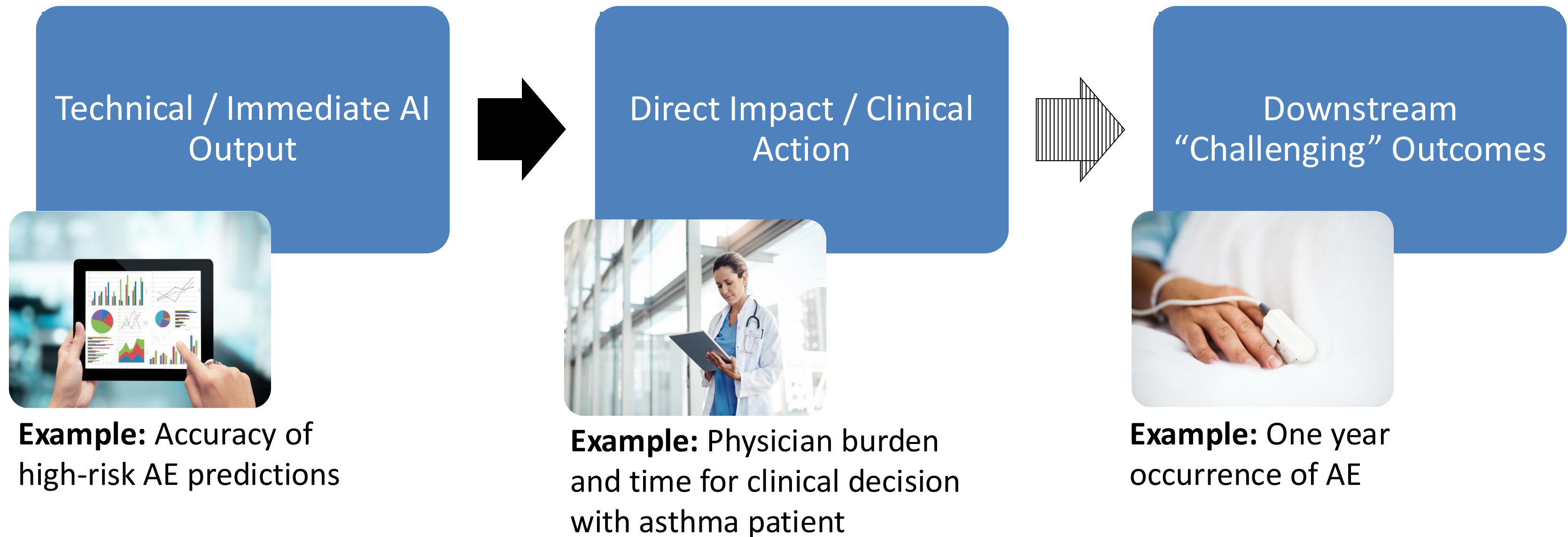
Benefit: Progressing beyond technical milestones to real world impact

Example: AI Scribes



Benefit: Progressing beyond technical milestones to real world impact

Example: Asthma exacerbation (AE) prevention

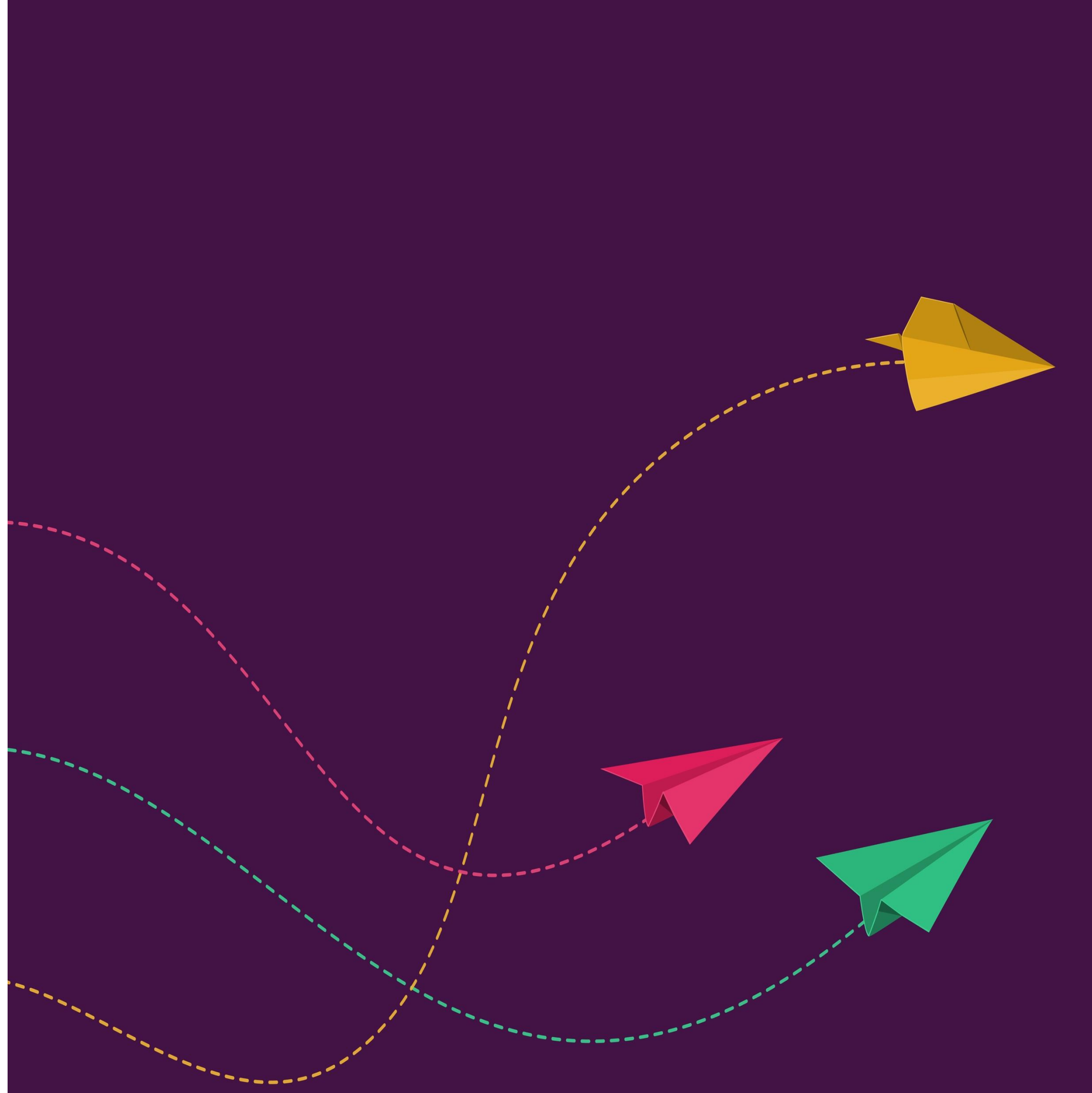


Many Outcomes to Consider

- Patient outcomes
- Provider outcomes
- System-level outcomes
- Care team communication and effectiveness
- Cost-effectiveness
- Safety, security
- Environmental considerations
- Health equity and fairness
 - Do all subpopulations experience similar outcomes
 - Who/where does or does not have access to high-quality, safe AI tools?

Note even a “perfectly” performing AI tool from a technical lens may not have real world impact

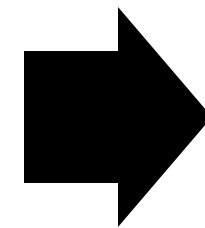
- **Need more high-quality primary care prospective evaluation studies!**



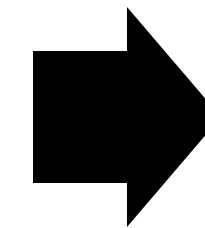
Challenge: AI performance changes across location, time, populations

Need post-deployment ongoing monitoring of performance and impact

Technical / Immediate AI
Output



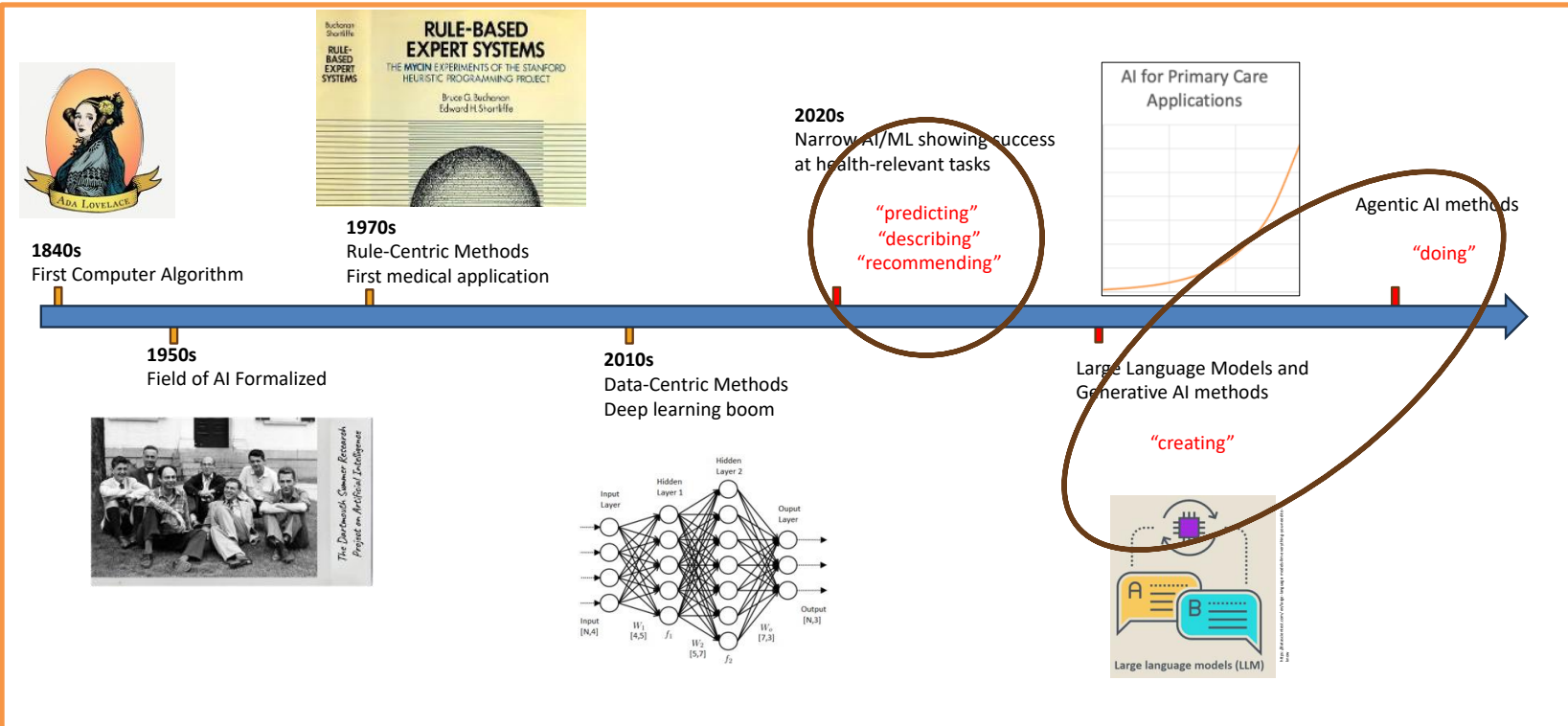
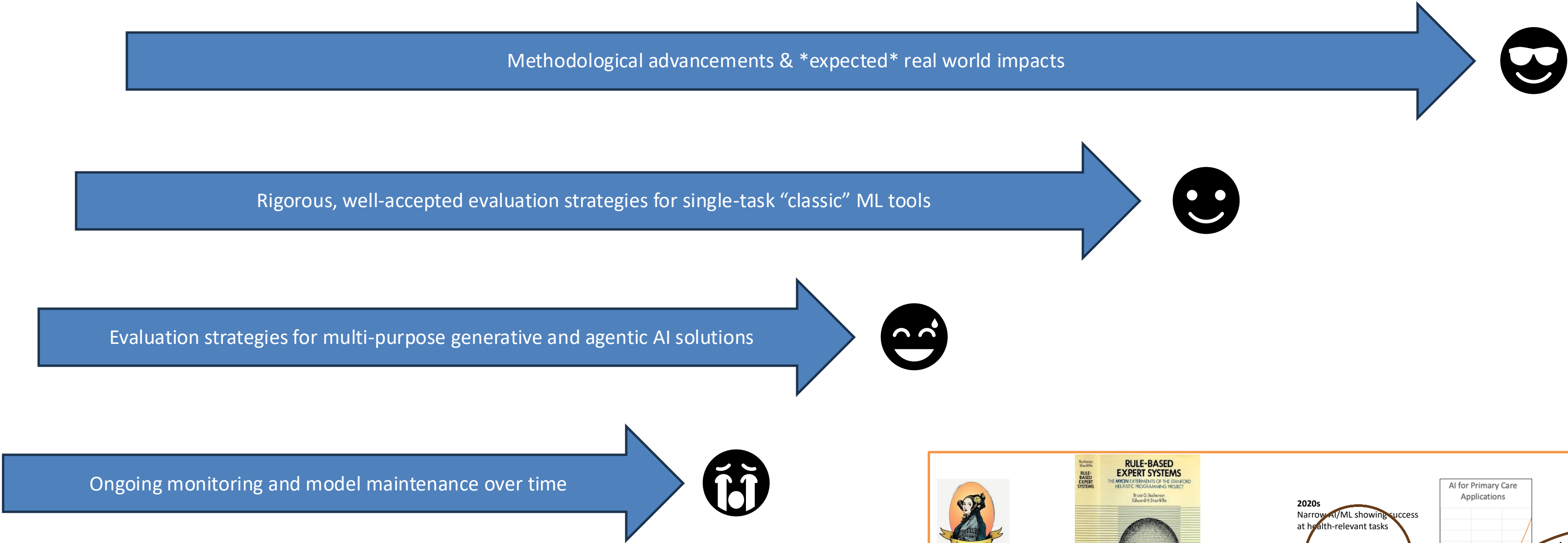
Direct Impact / Clinical
Action



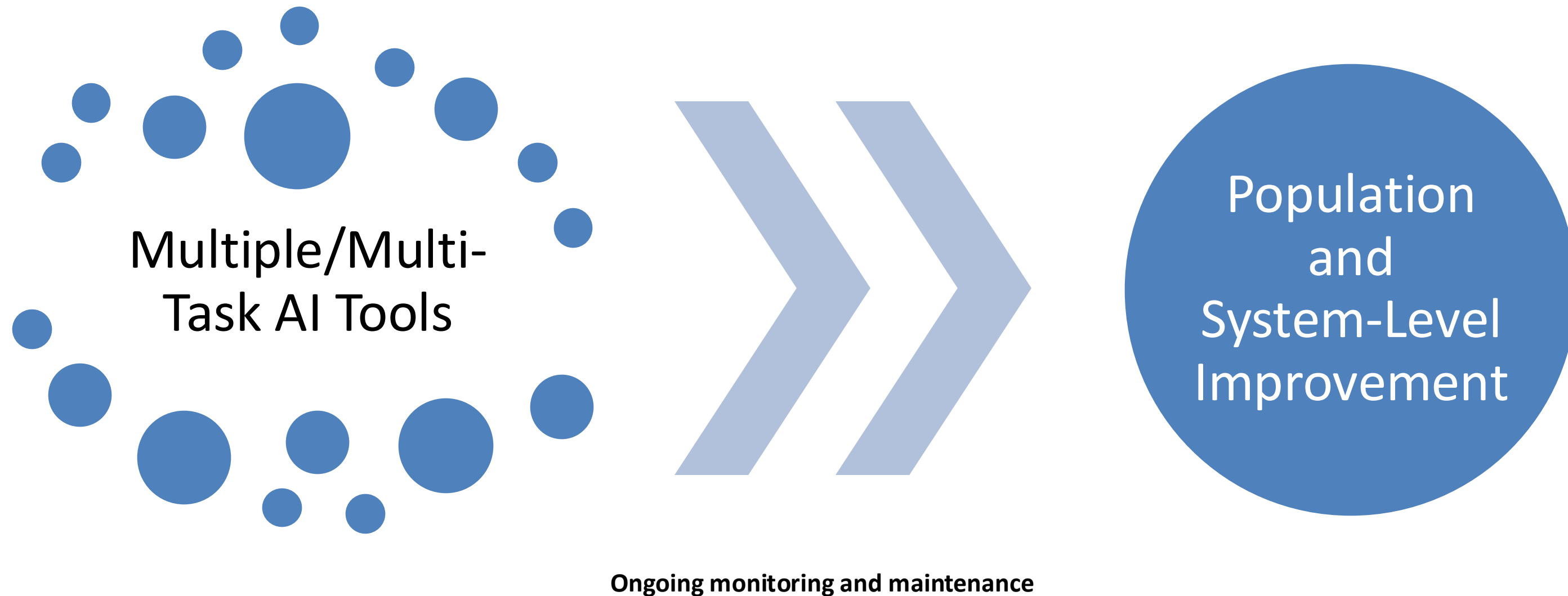
Downstream
“Challenging” Outcomes



Challenge: Methodological advancements and the availability of (not necessarily high quality) AI tools have outpaced evaluation & monitoring strategies



Challenge: Beyond single tool/task evaluation & monitoring strategies

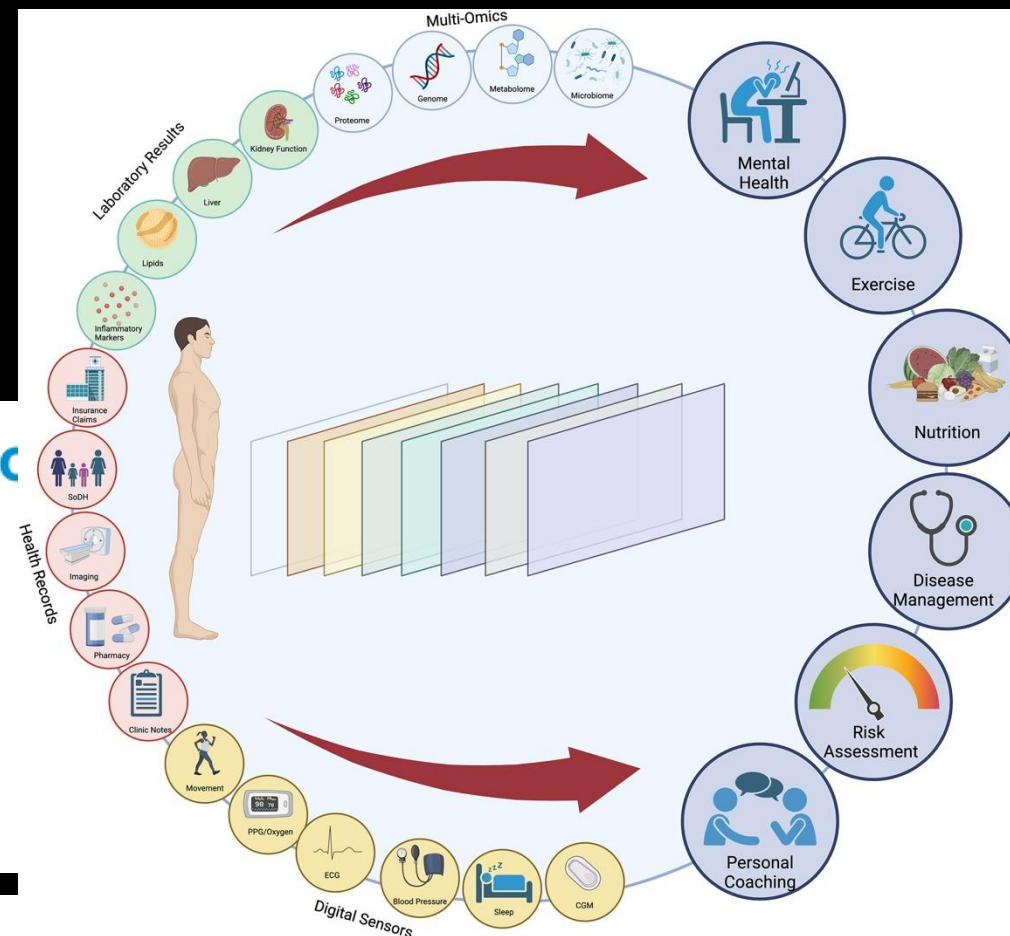


Lots of excitement.
Several challenges.
Largescale success TBD.

CellPress **Cell Metabolism**

Review
Transforming the cardiometabolic disease landscape: Multimodal AI-powered approaches in prevention and management

Evan D. Muse^{1,2} and Eric J. Topol^{1,2,*}
¹Scripps Research Translational Institute, Scripps Research, La Jolla, CA 92037, USA
²Division of Cardiovascular Diseases, Scripps Clinic, La Jolla, CA 92037, USA



PERSPECTIVE

Why Is Primary Care Different? Considerations for Machine Learning Development with Electronic Medical Record Data

Jacqueline K. Kueper¹, Ph.D.,¹ Winston Liaw², M.D., M.P.H.,² Daniel J. Lizotte³, Ph.D.,^{3,4} and Sian Hsiang-Te Tsuei⁵, M.D., Ph.D., C.C.F.P.⁵

Received: 3 November 2022

Perspective

Foundation models for generalist medical artificial intelligence

<https://doi.org/10.1038/s41586-023-05881-4>

Received: 3 November 2022

Michael Moor^{1,6}, Oishi Banerjee^{2,6}, Zahra Shakeri Hossein Abad³, Harlan M. Krumholz⁴, Jure Leskovec¹, Eric J. Topol^{5,7,8} & Pranav Rajpurkar^{2,7,8}

Towards Generalist Biomedical AI

Tao Tu^{*,†,1}, Shekoofeh Azizi^{*,†,2},
Danny Driess², Mike Schaeckermann¹, Mohamed Amin¹, Pi-Chuan Chang¹, Andrew Carroll¹,
Chuck Lau¹, Ryutaro Tanno², Ira Ktena², Basil Mustafa², Aakanksha Chowdhery², Yun Liu¹,
Simon Kornblith², David Fleet², Philip Mansfield¹, Sushant Prakash¹, Renee Wong¹, Sunny Virmani¹,
Christopher Semturs¹, S Sara Mahdavi², Bradley Green¹, Ewa Dominowska¹, Blaise Aguera y Arcas¹,
Joelle Barral², Dale Webster¹, Greg S. Corrado¹, Yossi Matias¹, Karan Singhal¹, Pete Florence²,
Alan Karthikesalingam^{†,†,1} and Vivek Natarajan^{†,†,1}

¹Google Research, ²Google DeepMind

PERSPECTIVE

Evolution of Future Medical AI Models — From Task-Specific, Disease-Centric to Universal Health

Weizhi Ma¹, Ph.D.,¹ Bin Sheng², Ph.D.,^{2,3} Yang Liu², Ph.D.,^{1,4} Jing Qian², Psy.D.,⁵ Xiaoxuan Liu², Ph.D.,⁶
Jingshan Li², Ph.D.,⁷ David Ouyang², M.D.,⁸ Haibo Wang², M.B., B.S., M.P.H.,⁹ Atanas G. Atanasov², Ph.D.,^{10,11}
Pearse A. Keane², M.D.,^{12,13} Wei-Ying Ma², Ph.D.,¹ Yih-Chung Tham², Ph.D.,^{14,15,16,17} and Tien Yin Wong², M.D., Ph.D.^{14,1}

Received: March 17, 2024; Revised: May 4, 2024; Accepted: May 16, 2024; Published: July 12, 2024

Ethics and governance of artificial intelligence for health: Large multi-modal models

Risks to be addressed

What can be done, and by who

Development phase

Bias
Privacy

Labor concerns
Carbon and water footprints

Equal wages and support to data workers

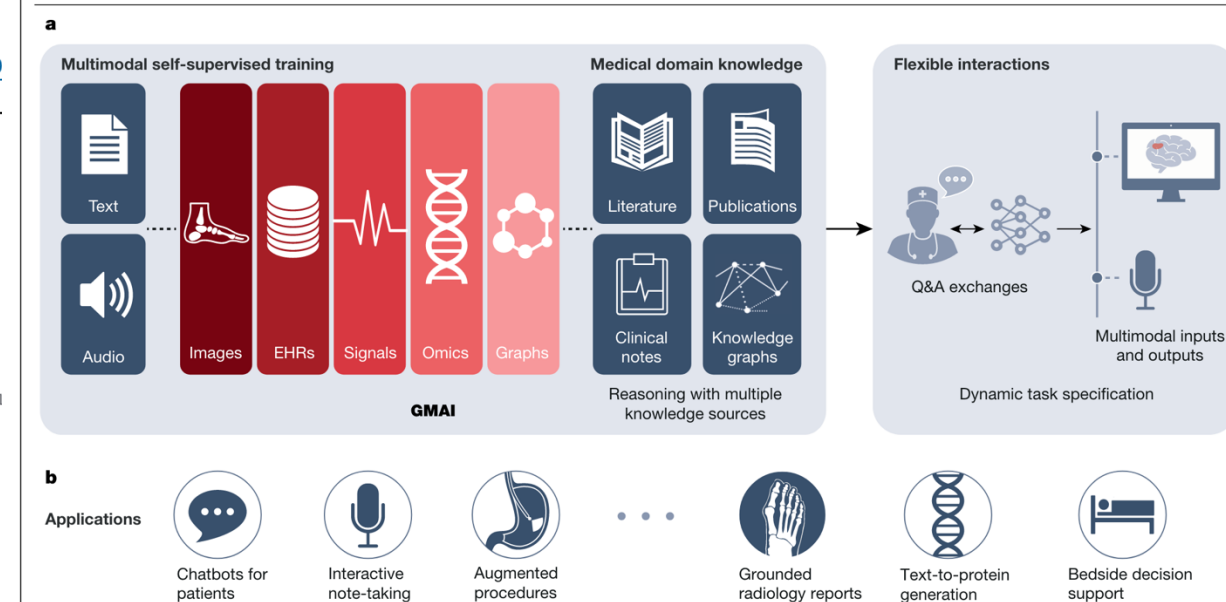
Developer actions

- Certification/training for programmers
- Data protection impact assessments
- Training data collected with 'best-practice' data protection rules
- Training data are refreshed, up-to-date, and context-appropriate
- Ensure transparency of training data
- Fair wages and support to data workers

Government actions

- Have and enforce strong data protection laws
- Issue target product profiles
- Mandate outcomes (predictability, interpretability, corrigibility, safety, cybersecurity)
- Introduce pre-certification programmes to identify and avoid ethical risks
- Conduct audits during early AI development
- Require developers to address carbon and water footprints
- Require developers to label AI-generated

Perspective



Regulations: Application approval; validation; audits; community-based challenges; analyses of biases, fairness and diversity

Fig. 1 | Overview of a GMAI model pipeline. a, A GMAI model is trained on out tasks that the user can specify in real time. For this, the GMAI model can

REVIEW ARTICLE

Not All Clinical AI Monitoring Systems Are Created Equal: Review and Recommendations

Jean Feng¹, Ph.D.,¹ Fan Xia², Ph.D.,¹ Karandeep Singh³, M.D.,² and Romain Pirracchio⁴, Ph.D., M.D.¹

Received: June 27, 2024; Revised: October 30, 2024; Accepted: November 21, 2024; Published: January 23, 2025

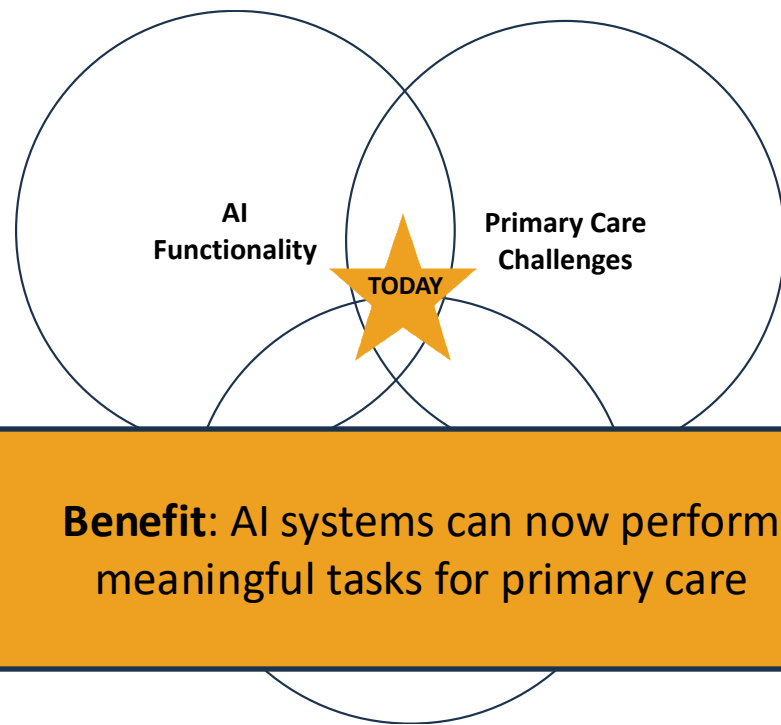
EDITORIAL

MAYO CLINIC PROCEEDINGS:
DIGITAL HEALTH

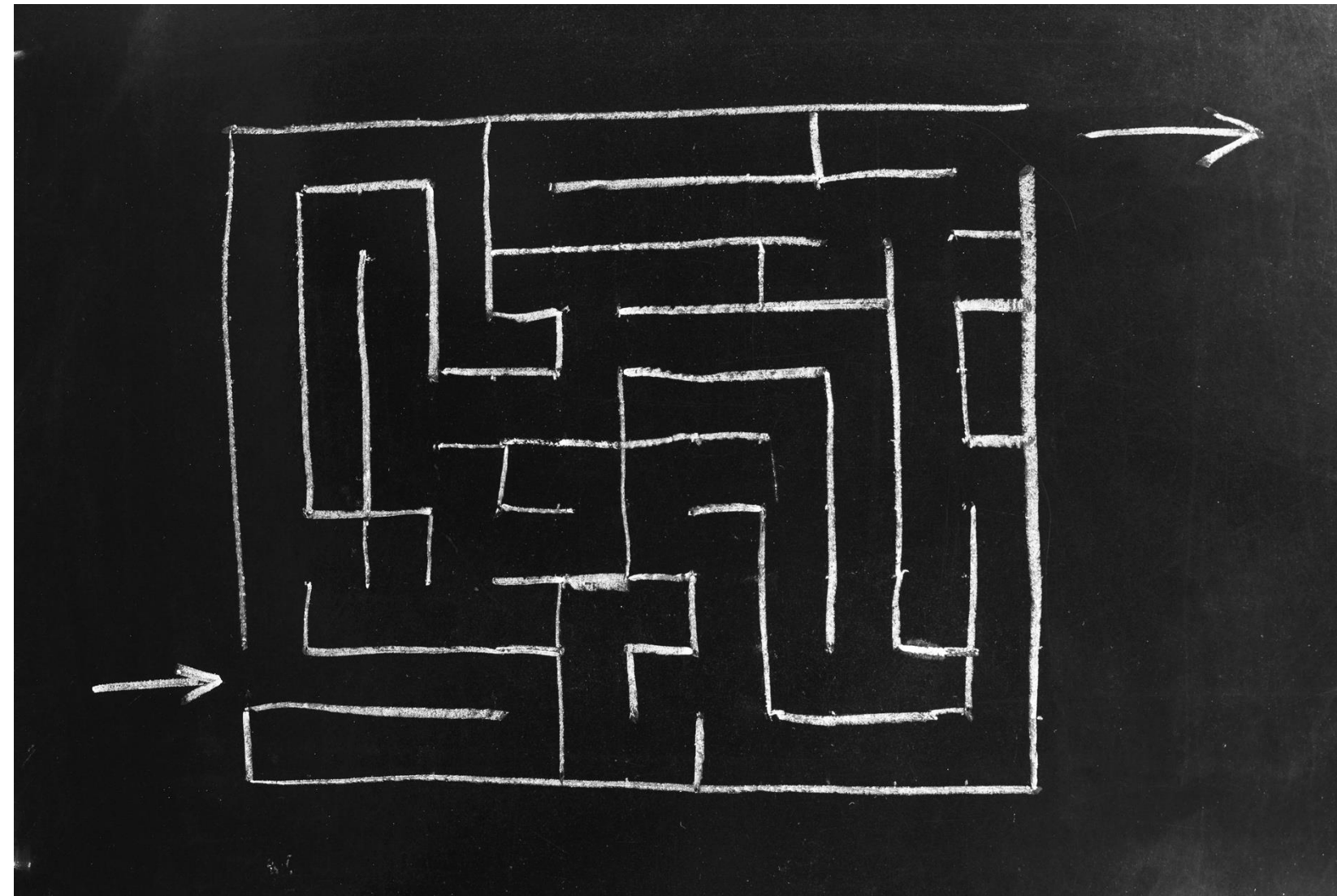


Complexities and Questions Toward
Artificial Intelligence for Diagnostic Support
in Virtual Primary Care

Summary



Benefit: AI systems can now perform meaningful tasks for primary care



Challenge: Evaluation and monitoring strategies to inform AI tool selection and maintenance over time

Longterm
Positive
Impact

?

Opportunity: Interdisciplinary primary care research teams have a lot to offer in this space!



AI in Primary Care

Teaching and Learning
Karim Hanna, MD, FAAFP, FAMIA



We Are Teachers.

- Benefit: Personalized, On-Demand Learning
- Challenge: The Risk of Misinformation and Overreliance

Board Prep

Family
Medicine

2024, Volume 56, Issue 9, 555-560, e-ISSN 1938-3800

ORIGINAL ARTICLE

Performance of Language Models on the Family Medicine In-Training Exam

Rana E. Hanna, BS^a; Logan R. Smith, BA^a; Rahul Mhaskar, PhD^b; Karim Hanna, MD^{a,c}

Results: ChatGPT 4.0 scored 167/193 (86.5%) with a scaled score of 730 out of 800. According to the Bayesian score predictor, ChatGPT 4.0 has a 100% chance of passing the family medicine board exam. ChatGPT 3.5 scored 66.3%, translating to a scaled score of 400 and an 88% chance of passing the family medicine board exam. Bard scored 64.2%, with a scaled score of 380 and an 85% chance of passing the boards. Compared to the national average of postgraduate year 3 residents, only ChatGPT 4.0 surpassed the residents' mean of 68.4%.

WE ARE TEACHERS



[nature](#) > [npj.digital.medicine](#) > [articles](#) > [article](#)

Article | [Open access](#) | Published: 18 March 2025

Preliminary analysis of the impact of lab results on large language model generated differential diagnoses

[Balu Bhasuran](#), [Qiao Jin](#), [Yuzhang Xie](#), [Carl Yang](#), [Karim Hanna](#), [Jennifer Costa](#), [Cindy Shavor](#), [Wenshan Han](#), [Zhiyong Lu](#) & [Zhe He](#) 

[npj Digital Medicine](#) **8**, Article number: 166 (2025) | [Cite this article](#)

were created, incorporating demographics, symptoms, and lab data. Five LLMs—GPT-4, GPT-3.5, Llama-2-70b, Claude-2, and Mixtral-8x7B—were tested to generate Top 10, Top 5, and Top 1 DDx with and without lab data. Results show that incorporating lab data enhances accuracy by up to 30% across models. GPT-4 achieved the highest performance, with Top 1 accuracy of 55% (0.41–0.69) and lenient accuracy reaching 79% (0.68–0.90). Statistically significant

OVERRELIANCE ON AI



Patient Learning

Table 2. Understandability and Actionability of Different LLM Responses Based on PEMAT-Q Rubric

	ChatGPT		Google Bard		Hugging Chat		Claude 2	
	Understandability	Actionability	Understandability	Actionability	Understandability	Actionability	Understandability	Actionability
Hypertension	67%	40%	33%	40%	67%	40%	67%	20%
Hyperlipidemia	67%	40%	56%	20%	67%	60%	67%	60%
Type 2 diabetes	67%	40%	44%	20%	56%	20%	67%	20%
Hypothyroidism	67%	40%	44%	20%	56%	20%	78%	60%
GERD	67%	20%	44%	20%	56%	20%	67%	40%
Atherosclerosis	67%	20%	67%	20%	56%	20%	56%	20%
Vaccination	78%	20%	78%	20%	44%	20%	78%	20%
Average	69%	31%	52%	23%	57%	29%	69%	34%
Standard deviation	4%	11%	16%	8%	8%	16%	8%	19%

Abbreviations: PEMAT-Q, Patient Education Materials Assessment Tool Question; GERD, gastrointestinal reflux disease.

PRiMER
peer-reviewed reports in medical education research

LEARNER RESEARCH

Artificial Intelligence-Prom

Mafaz Kattih | Max Bressler | Logan R. Smith | An

PRiMER. 2024;8:51.

Published: 9/17/2024 | DOI: 10.22454/PRiMER.2024.91608

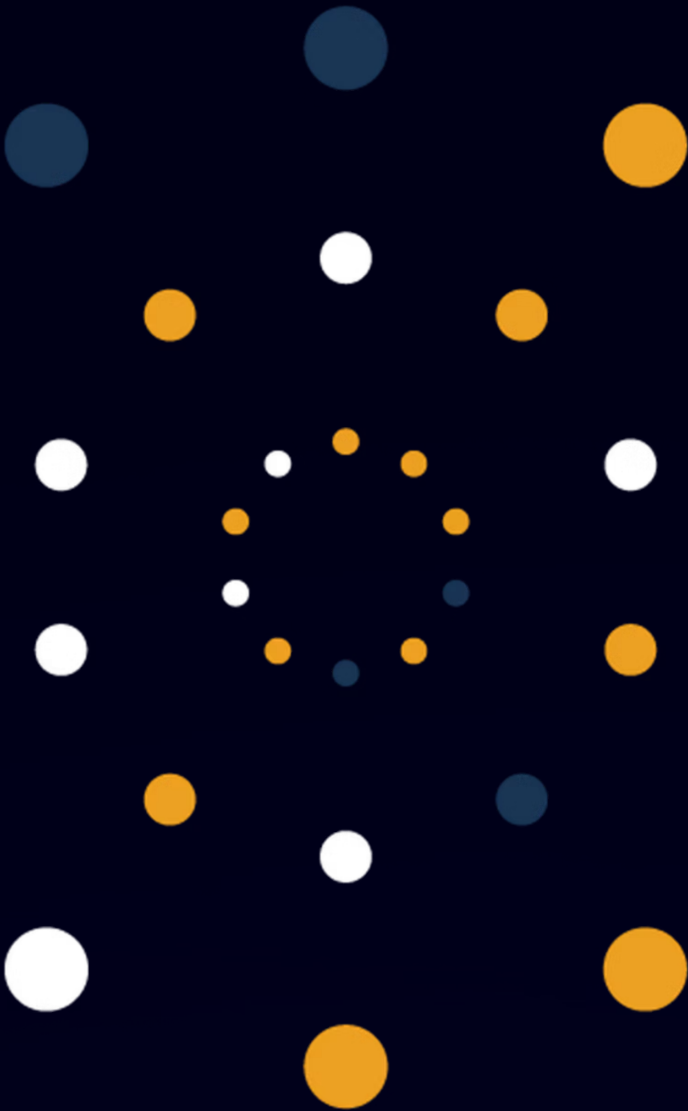


Thank You!



MedEd+AI





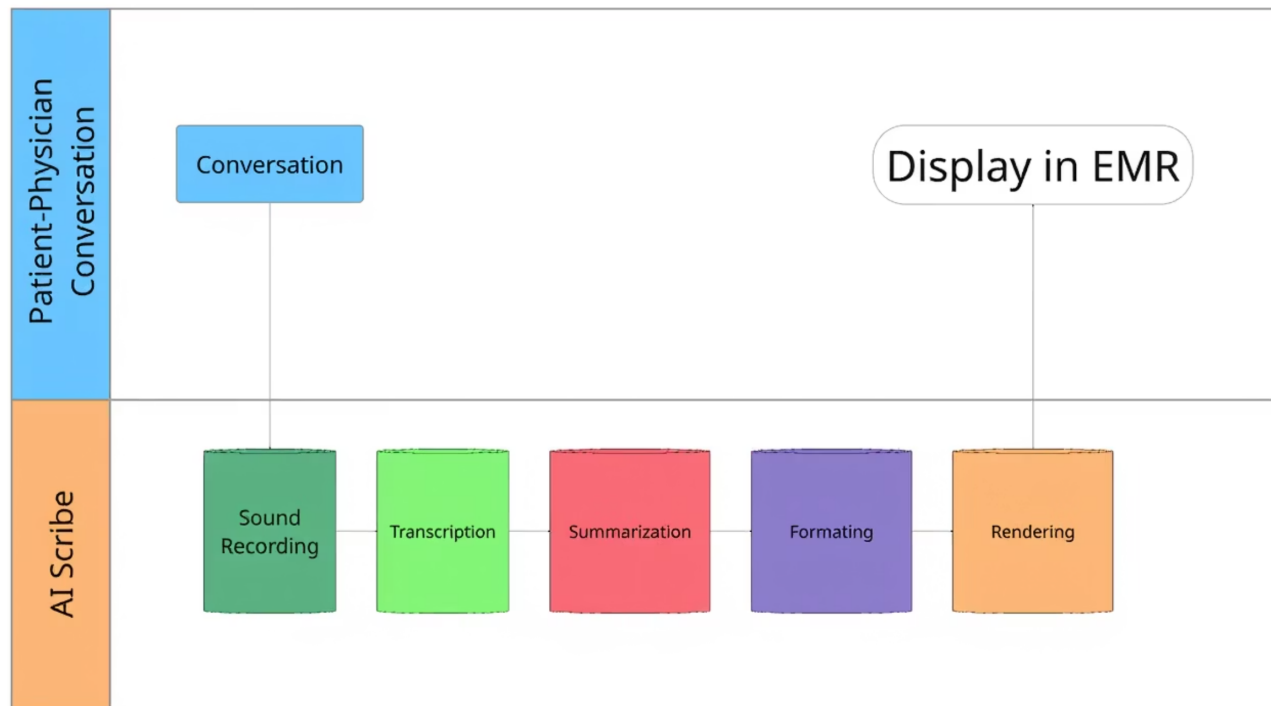
AI in Primary Care: Good governance is a challenge

Balancing innovation with governance in clinical settings

Karim Keshavjee MSc, MD, MBA Assistant Professor & Program
Director Master of Health Informatics Dalla Lana School of Public
Health University of Toronto, Canada

NAPCRG

AI Scribe Data Flow





The Governance Gap



Small practices lack hospital resources

No legal counsel, privacy officers, or data committees



Clinicians as gatekeepers

Responsible without proper tools or authority



Equity concerns

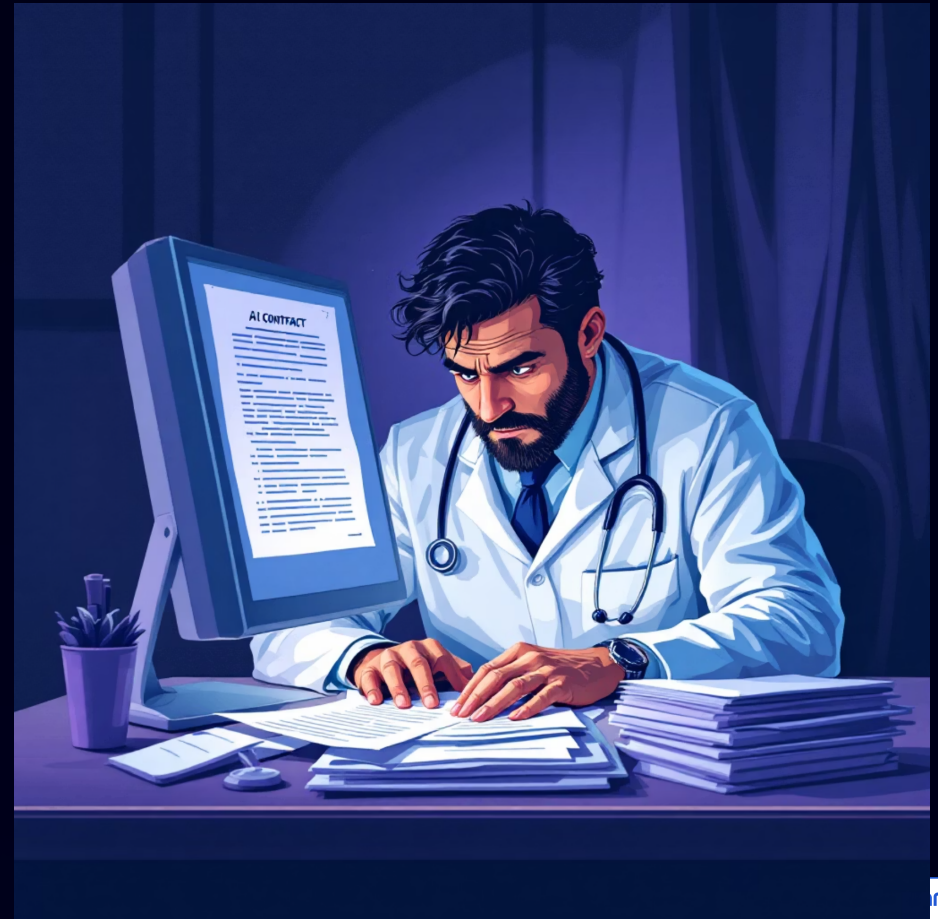
Rural and under-resourced areas face heightened risks

Key Challenge: Risk Without Support

Clinicians remain legally responsible for AI they cannot properly evaluate

AI reaches clinics through informal channels

Oversight is patchy, risk unmanaged





Proposed Solution: Two-Layer Governance



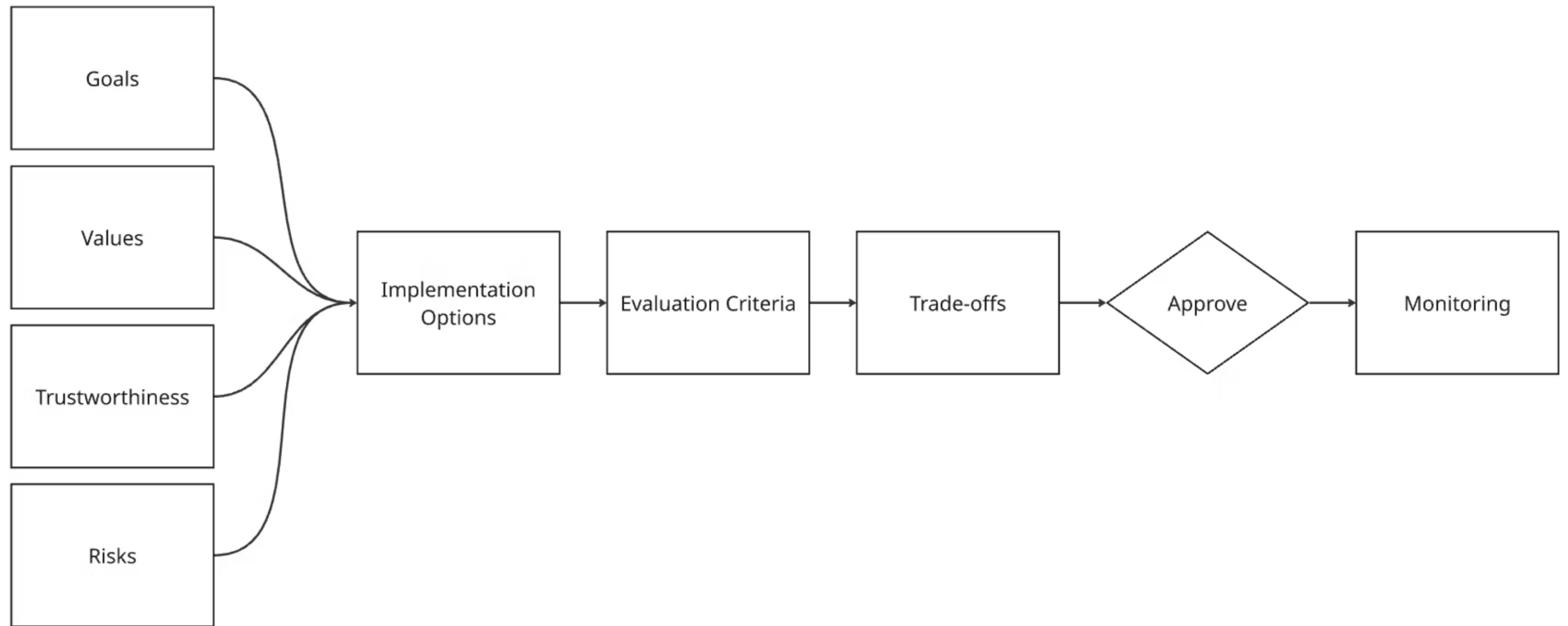
National AI Committee

Certifies tools, sets guidelines, maintains registry



Local AI Governance Boards

Reviews implementation, assesses workflow fit, identifies local risks



Key Benefit: Enhanced Patient Care



Sharper Diagnosis

AI improves diagnostic accuracy



Reduced Paperwork

Automated documentation saves time



Tailored Treatment

Personalized care recommendations



The Path Forward

Sustainable Implementation

- Risk-matched governance
- Vendor-paid certification fees
- Standardized education

