

Organizational Governance of Al

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Learning Objectives

- 1. Define common terminologies and lay the foundations related for healthcare AI
- 2. Identify common stages and decision points that healthcare organizations navigate along the AI product lifecycle.
- 3. Describe the implementation of best practices throughout the AI product lifecycle at Duke Health.
- 4. Specify organizational capabilities and processes required to govern the use of AI products.
- 5. Lay out the technical infrastructure, personnel requirements, and frontline clinician support required to implement AI products within clinical care



Duke Institute for Health Innovation

Terminology

Big data and AI in healthcare

Health AI Partnership (HAIP)

Key Decision Points in Al Adoption

Organizational Governance of Al



2 mins

3 mins

2 mins

3 mins

15 mins

15 mins

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Duke Institute for Health Innovation





Duke Institute for Health Innovation (DIHI)

Our mission: Catalyze innovations at Duke

Catalyze transformative innovation in health and healthcare through high-impact research, leadership development and workforce training and the cultivation of a community of entrepreneurship

Our approach: Innovation by design

Understand user workflow, desired outcomes and problems (needs) and then collaboratively develop concepts and prototypes, and iterate through to finalize solution



DIHI domains of innovation

DIHI **Duke Institute for Health Innovation**

Implementation and Health **Delivery Science**

- Catalyze • multidisciplinary teamwork
- New care models
- Structured interface to Duke Health
- Living laboratory to incubate, refine, validate, and scale new ideas

Health Technology Innovation

- Leverage a growing health data infrastructure
- Create a connected digital health ecosystem
- Collaboration and co-development of technology
- Responsible development of datascience solutions

Leadership and Workforce **Development**

• Train current and future leaders across health care : • Leadership management • Innovation Quantitative health sciences Contribute to developing the workforce of the

future



Best Practices Development and Dissemination

- **Disseminate best** practices derived through internal R&D to elevate health innovation across ecosystem
- Convene stakeholders across settings to address common challenges in health innovation

Industry best-practice approach in catalyzing innovation

IJ

RFA

DIHI RFA approach

"Top-down + Bottom-Up" approach to sourcing innovations

- Duke Health leadership develops mission-aligned strategic themes for innovation
- Front-line faculty and staff propose "problems" aligned with strategic themes and novel solutions
- Systematic review and due diligence: Assessments on team, feasibility, resource needs, impact and value to patients
- Operational Lead engaged right from the proposal stage
- 8-12 innovations funded each year; Duration: 12-15 months
- DIHI members embedded within project innovation teams to rapidly catalyze the innovations
- Pivots as needed to support rapid evolution to create value
- Metrics: clinical utility, economic utility, cultural impact, IP and academic outputs



DIHI Innovation Jam

A Health focused Shark Tank at Duke

Solicits and identifies high-potential healthcare and health innovations ready for commercialization

Duke Leadership as Sharks:

 DUHS leaders, Department Chairs, Deans of School of Medicine, Nursing, Engineering, OLV, I&E, MedBlue, Center and Institute Directors

Innovation proposals from students, faculty, trainees and staff across campus

Funding to support entrepreneurship / formation of company and also develop the product/service etc.

Inventors offer portion of their share of Duke internal returns for investment from the sharks

Internal syndicated investment agreements documented through MOUs.



Industry best-practice approach in catalyzing innovation





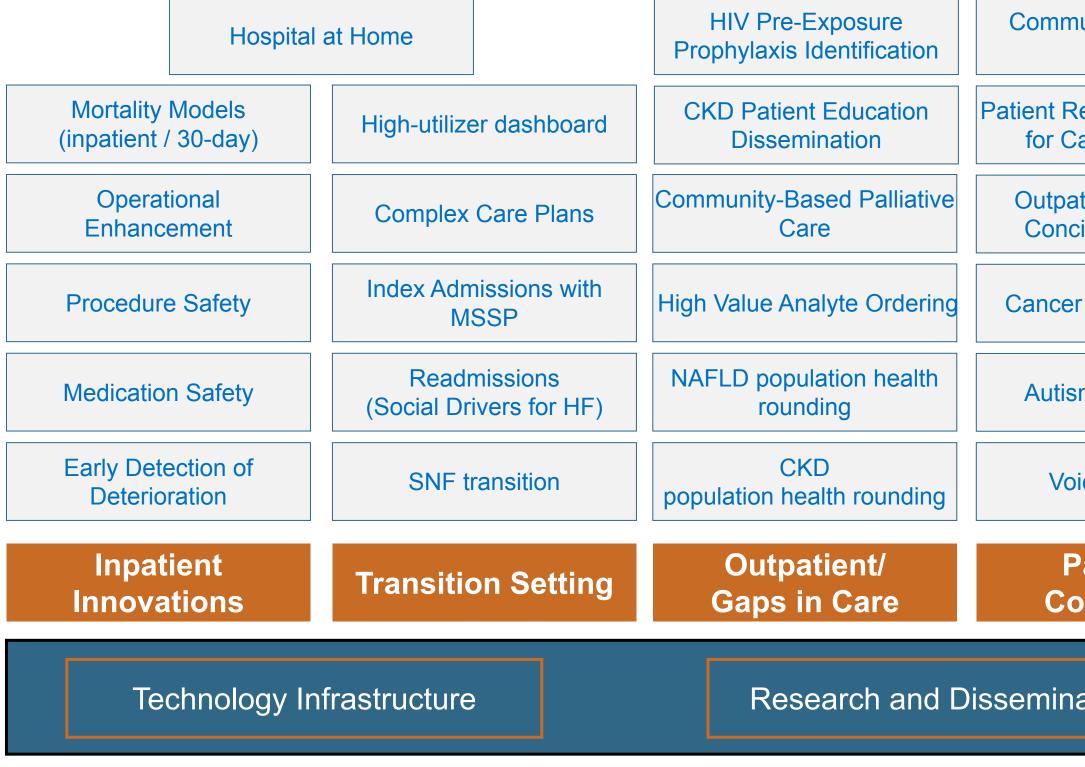
@dukeinnovate

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Duke Institute for Health Innovation

NOVEMBER 3, 2023

DIHI spectrum of value creation



Duke Institute for Health Innovation [DIHI] – Spectrum of value creation across the ecosystem



nation	Education and Training		
Patient & ommunity	Immersion in innovation and data science		
pices of Duke	Journal Club		
sm and Beyond	Case Studies and Data Camp		
er Distress Coach	 Summer Fellowship in Data Science 		
atient Procedure cierge Program	course in BME		
Reported Outcomes Cancer Patients	 Data Science in Health masters 		
nunity COVID-19 Support	 Medical Students Scholarship 		

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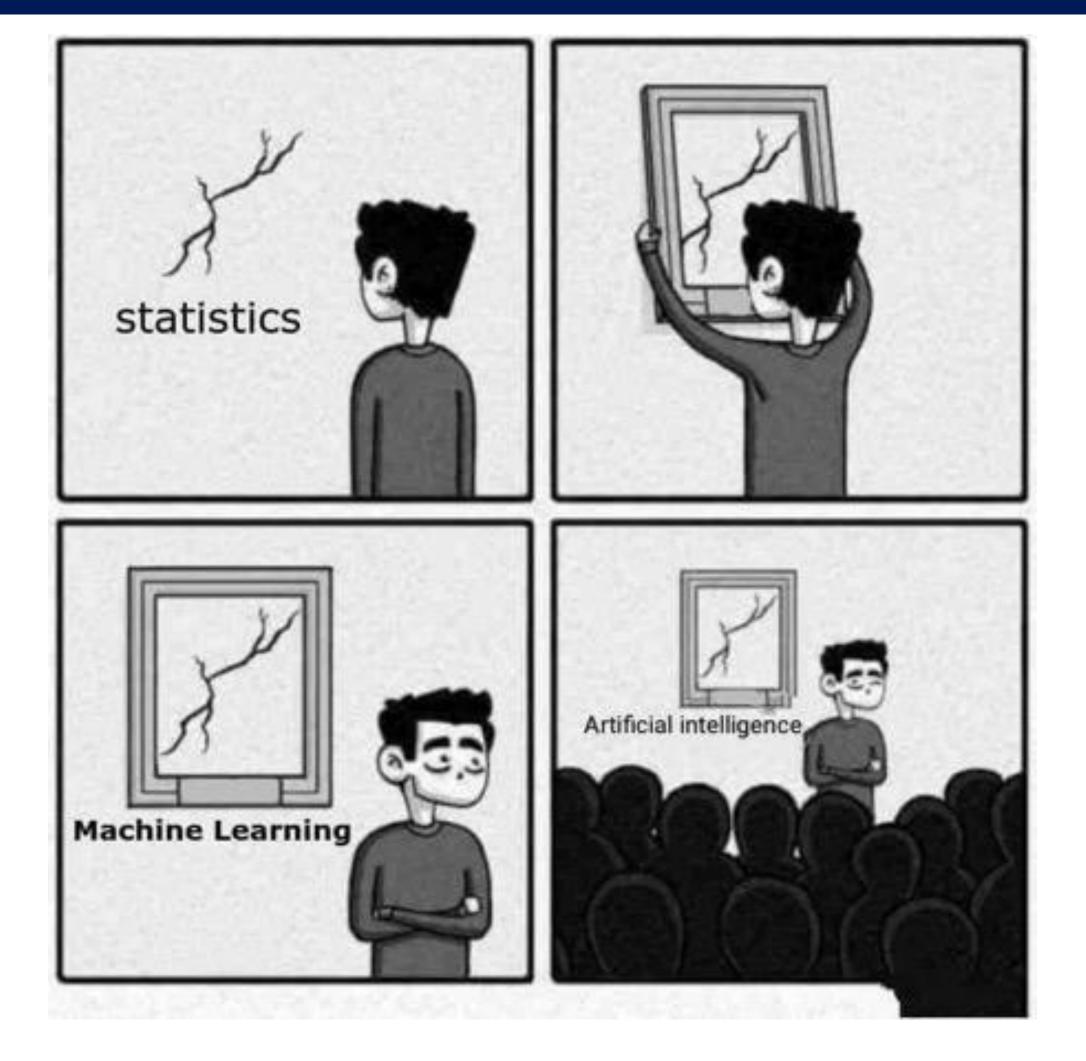
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3 mins

15 mins

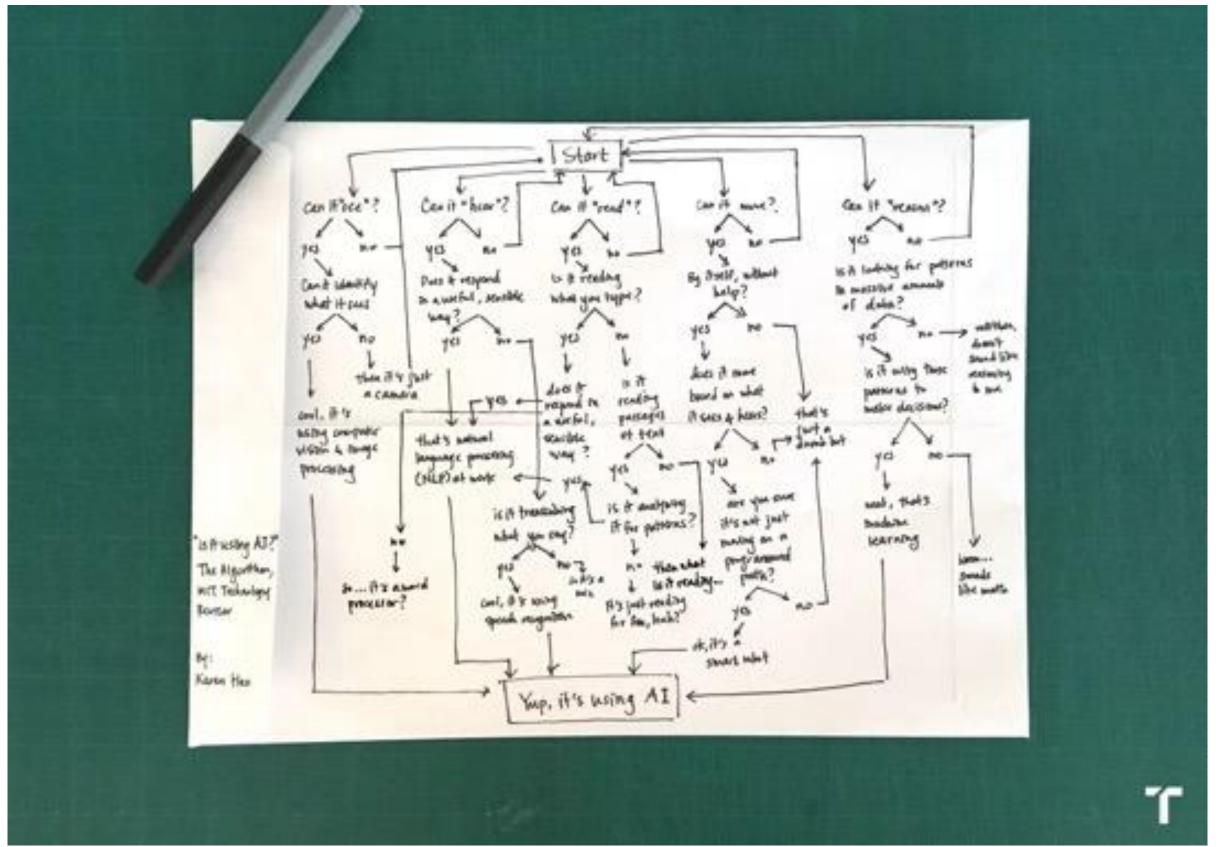
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What is Al?



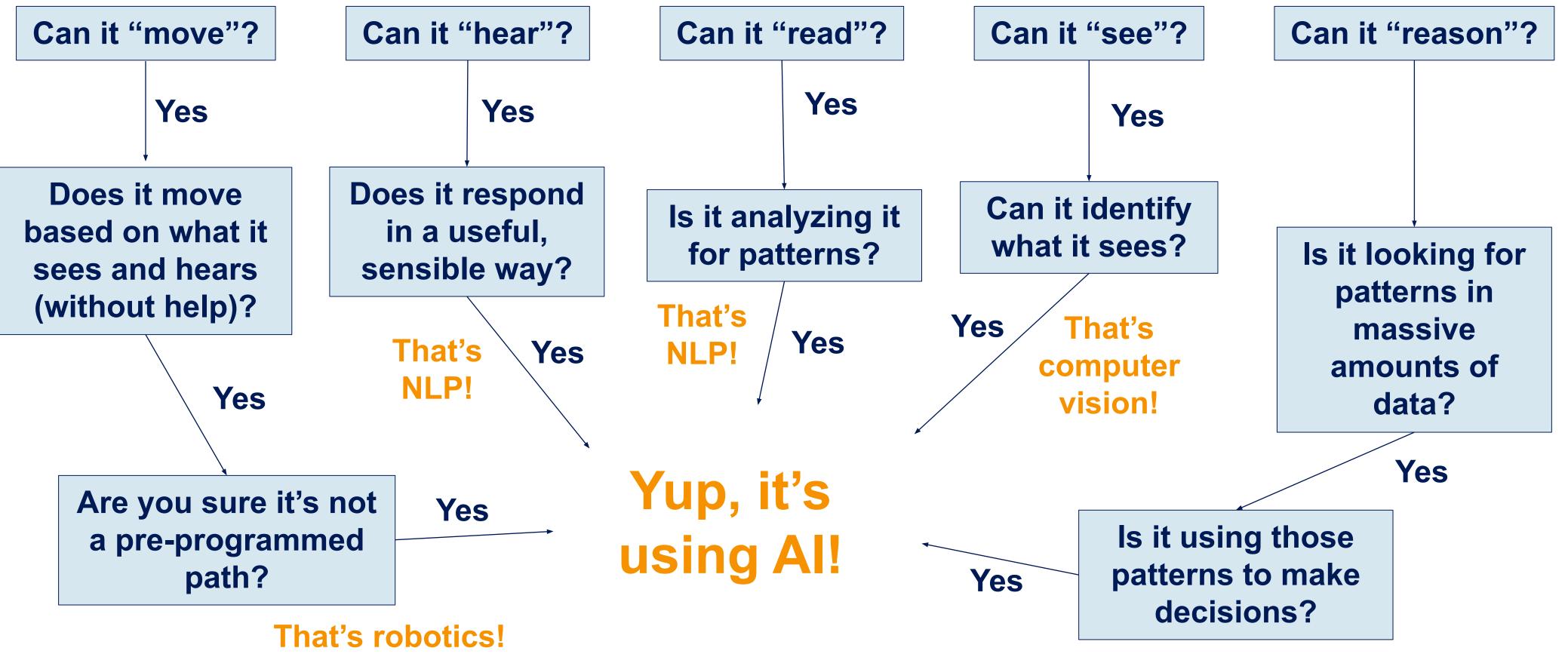
https://www.technologyreview.com/2018/11/10/139137/is-this-ai-we-drew-you-a-flowchart-to-work-it-out/

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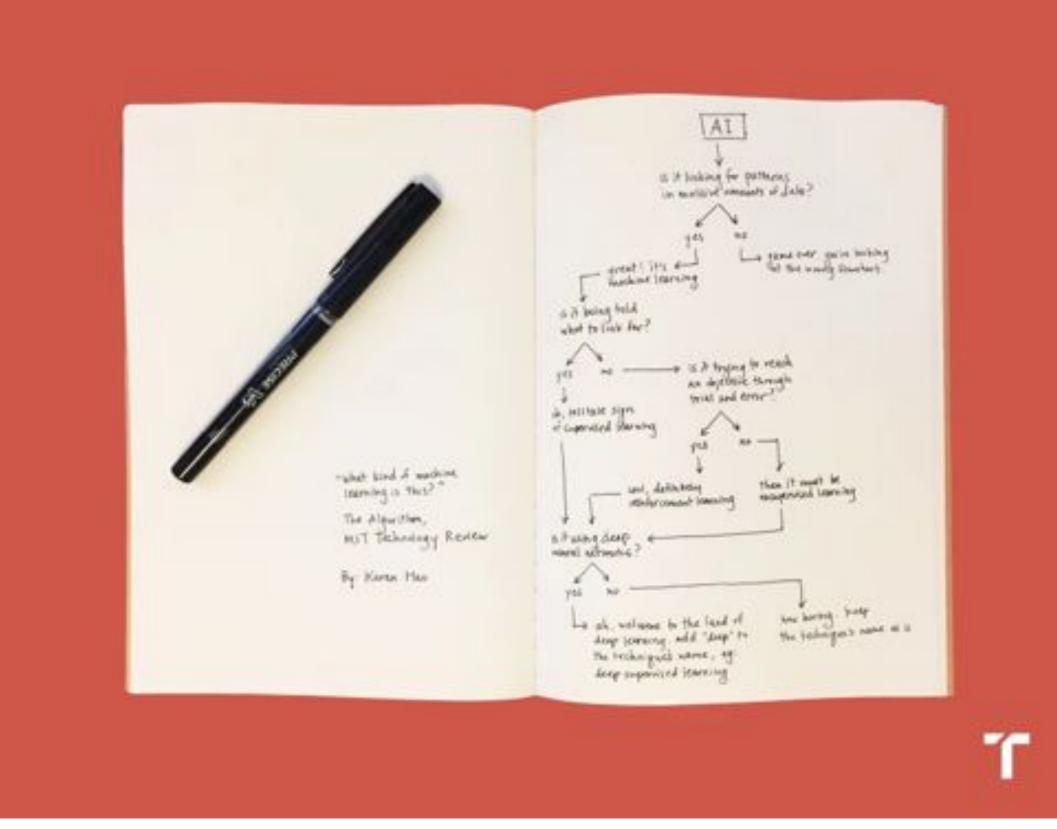
What is Al?



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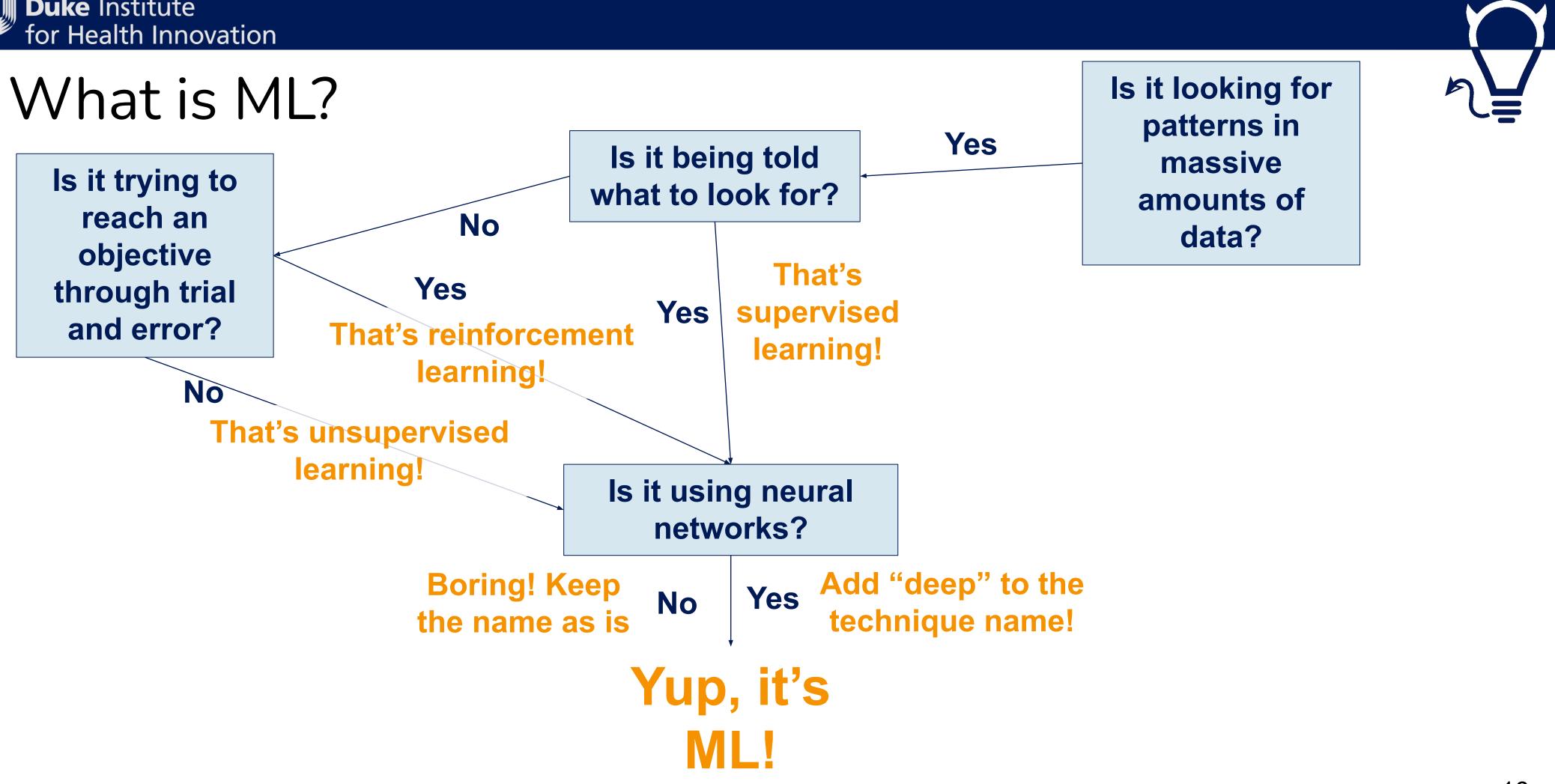
What is Machine Learning (ML)?



https://www.technologyreview.com/2018/11/17/103781/what-is-machine-learning-we-drew-you-another-flowchart/

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https://www.technologyreview.com/2018/11/10/139137/is-this-ai-we-drew-you-a-flowchart-to-work-it-out/

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What is Generative Al

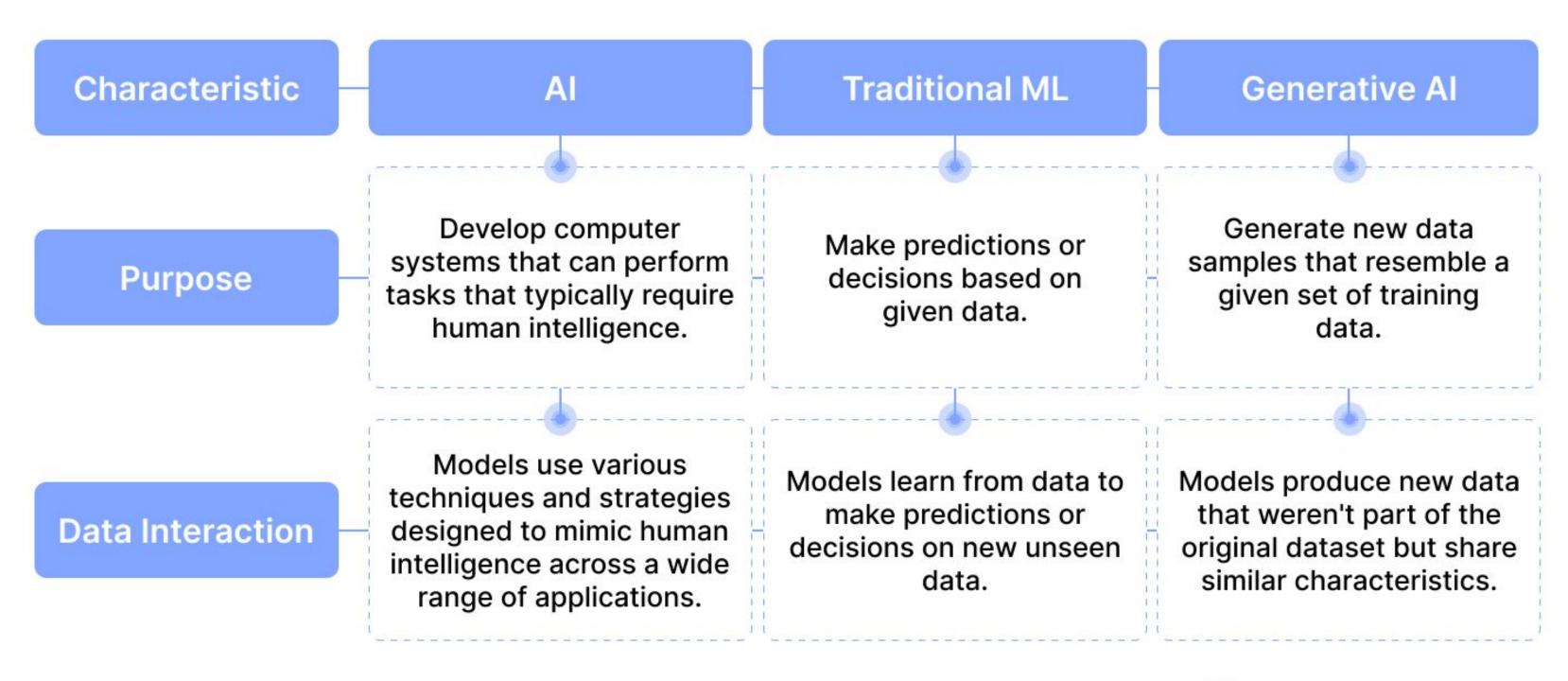
Generative AI refers to a type of deep-learning artificial intelligence technology that can generate new content, from text to images, sound, and videos, based on the data it has learned from.

It uses patterns and information from vast amounts of data to create new, similar data.

Examples: Chatbots, image generators, music composition.



Artificial Intelligence vs. Traditional Machine Learning, Generative AI



Reference: https://www.techopedia.com/definition/34633/generative-ai







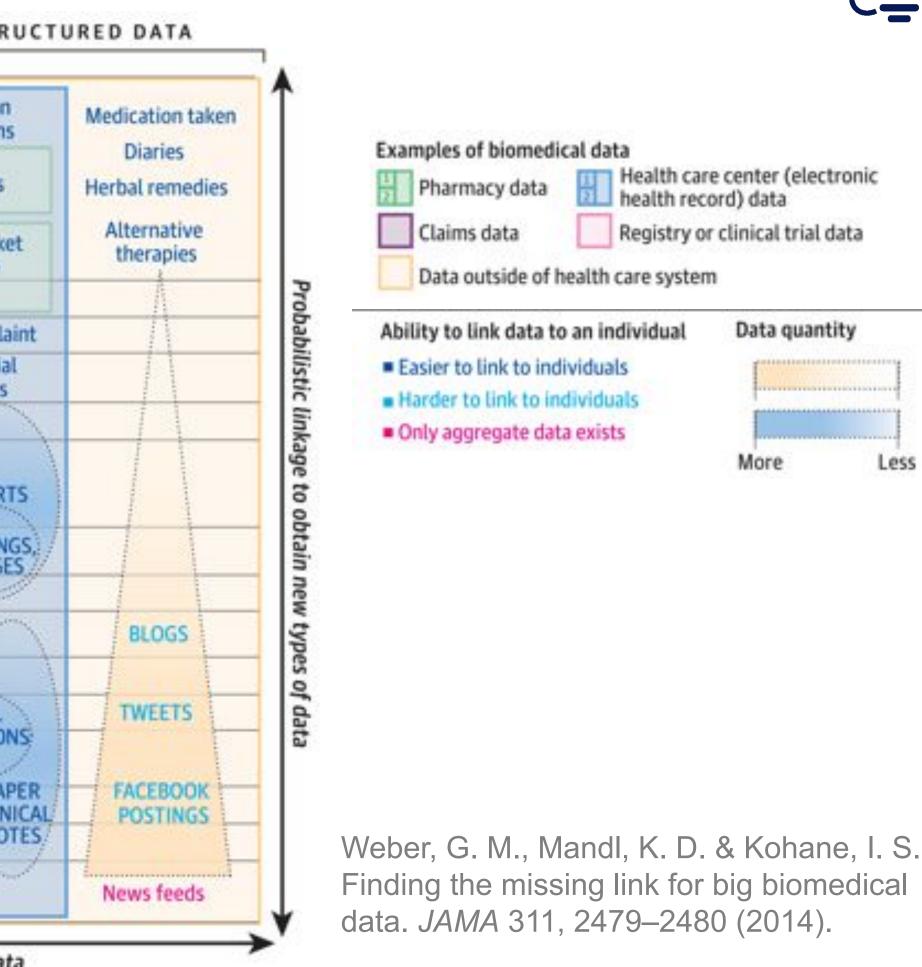
What is data?

TYPES OF DATA					UNSTRUCTU	
	Electronic 1 Medication pill dispensers prescribed			2	Medication instructions	
Medication	1 OTC Medication fill		Dose Route		Allergies	
	2		NDC RxNorm		Out-of-pocket expenses	
Demographics	/		HL7			
Encounters	/ \	Employee sick days	Visit type and time		Chief complaint	
Diagnoses		Death records	SNOMED ICD-9		Differential diagnosis	
Procedures			CPT ICD-9			
Diagnostics (ordered)	PERSONAL HEALTH RECORDS	HOME TREATMENTS, MONITORS, TESTS	LOINC Pathology, histology ECG Radiology		REPORTS	
Diagnostics (results)			Lab values, vital signs		TRACINGS,	
Genetics	PATIENTS	23andMe.com	SNPs, arrays			
Social history	LIKEME.COM	Police records	Tobacco/alcohol use		DIGITAL	
Family history	1 1	Ancestry.com			CLINICAL NOTES	
Symptoms	1 /	Indirect from OTC purch			PHYSICAL	
Lifestyle	Fitness club memberships, grocery store purchases CREDIT CARD PURCHASES			EXAMINATIONS		
Socioeconomic		Census records, Zillow,			PAPER	
Social network		Facebook friends, Twitte	er hashtags		NOTES	
Environment		Climate, weather, publi HealthMap.org, GIS ma				

Probabilistic linkage to validate existing data or fill in missing data



Less



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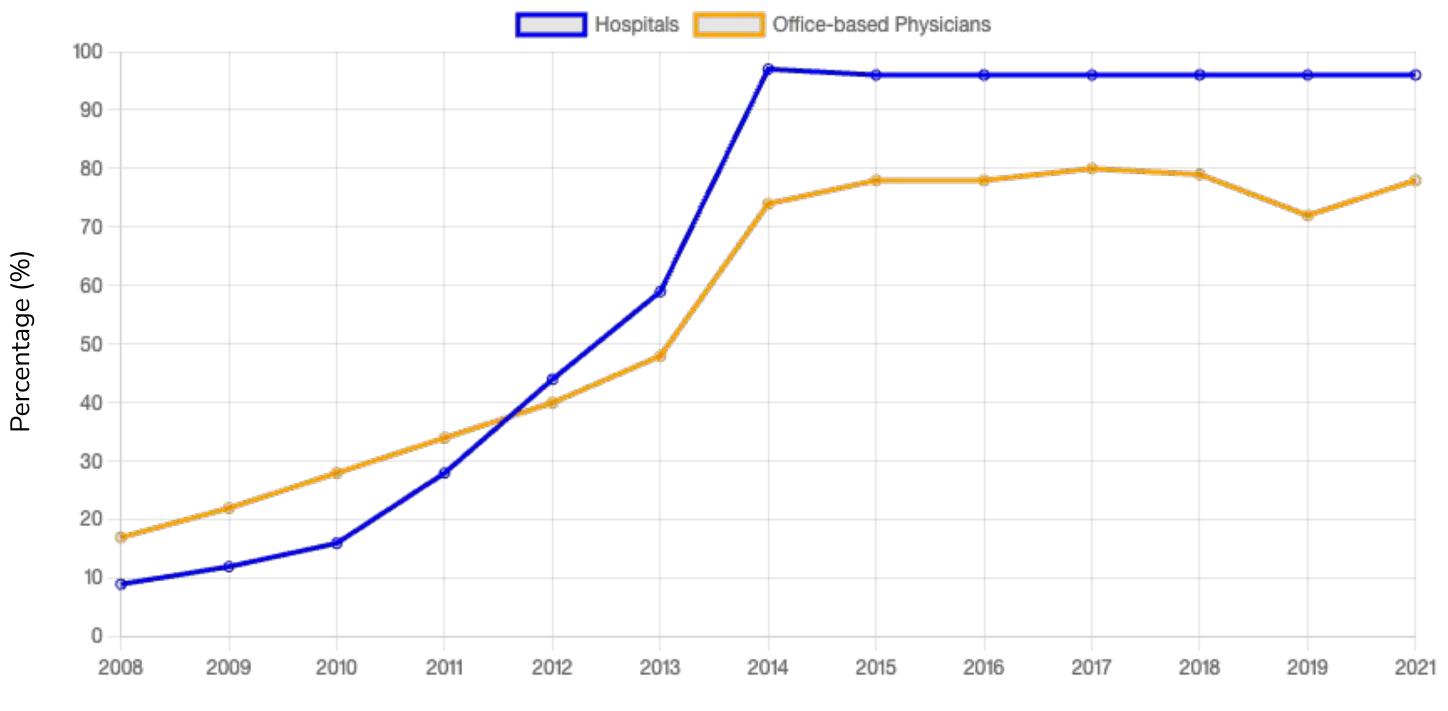
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15 mins

15 mins

Adoption of Electronic Health Records (EHR) in US



Year



Excitement about using AI in healthcare delivery



500+ medical AI systems

July 2022

DIHI





$3,569 \rightarrow 50,000+$ in 2010 in 2022

de Hond AAH, Leeuwenberg AM, Hooft L, Kant IMJ, Nijman SWJ, van Os HJA, et al. Guidelines and quality criteria for artificial intelligence-based prediction models in healthcare: a scoping review. NPJ Digit Med. 2022;5(1):2.

Jungblut L, Blüthgen C, Polacin M, Messerli M, Schmidt B, Euler A, et al. First Performance Evaluation of an Artificial Intelligence-Based Computer-Aided Detection System for Pulmonary Nodule Evaluation in Dual-Source Photon-Counting Detector CT at Different Low-Dose Levels. Invest Radiol. 2022;57(2):108-14.

Al in healthcare delivery

- Informing therapeutic and diagnostic decisions [1-2] ${ \bullet }$
- Prioritizing healthcare resources
 - Enrollment in care management programs [3]
 - Surgery scheduling [4]
 - Organ transplantation [5]

[1] Badgeley MA, Zech JR, Oakden-Rayner L, et al. Deep learning predicts hip fracture using confounding patient and healthcare variables. NPJ digital medicine. 2019;2:31.

preprint 2018;arXiv:1807.00431v2.

[3] Rumsfeld JS, Joynt KE, Maddox TM. Big data analytics to improve cardiovascular care: promise and challenges. Nature Reviews Cardiology. 2016;13(6):350-9.

[4] Murray SG, Wachter RM, Cucina RJ. Discrimination by artificial intelligence in a commercial electronic health record—a case study. Health Affairs Forefront. January 2020. (https://www.healthaffairs.org/content/forefront/discrimination-artificial-intelligence-commercial-electronic-health-record-case-study.)

2021:12:694222.



[2] Zech JR, Badgeley MA, Liu M, Costa AB, Titano JJ, Oermann EK. Confounding variables can degrade generalization performance of radiological deep learning models. arXiv

[5] Clement J, Maldonado AQ. Augmenting the transplant team with artificial intelligence: Toward meaningful AI use in solid organ transplant. Frontiers in immunology.

Benefits of using AI in healthcare delivery

- Operational benefits
 - Cost savings by USD 150 billion in 2026
- Care delivery benefits from proactive (vs. reactive) health management
 - Earlier diagnosis
 - Tailored treatments
 - More efficient follow-ups
 - Fewer hospitalizations
 - Less doctor visits
 - Less treatments



Bohr A, Memarzadeh K. The rise of artificial intelligence in healthcare applications. Artificial Intelligence in Healthcare. 2020;25-60. doi:10.1016/B978-0-12-818438-7.00002-2

Al adoption in healthcare delivery However, few AI tools are used in clinical care in reality.

Census data (2022)

- Less than 5% of healthcare organizations in the US are using AI tools.
- Fewer than 1,000 jobs in healthcare are related to machine learning and Al.

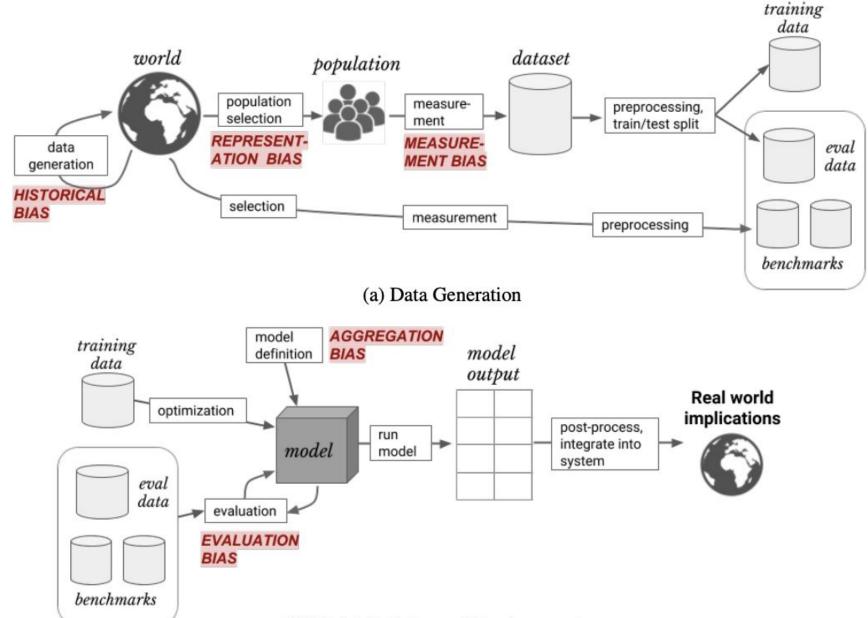


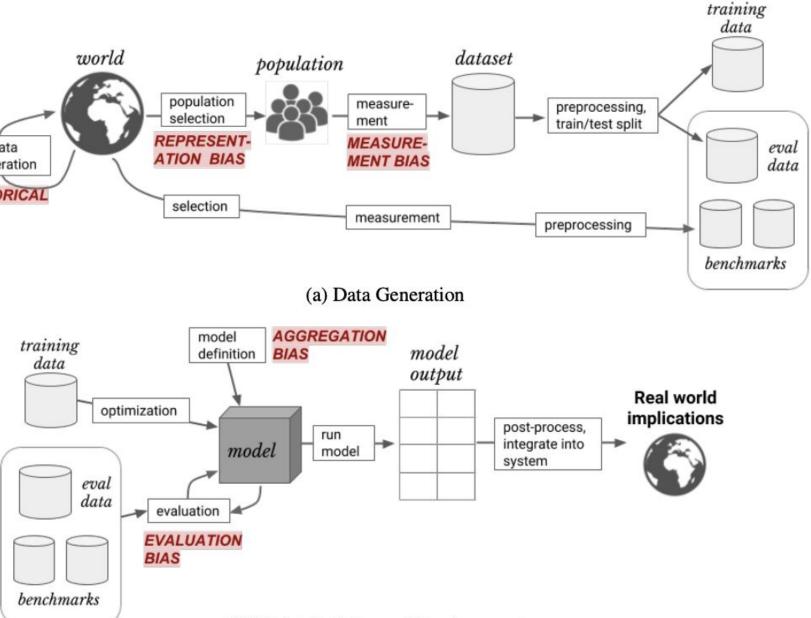
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Challenges of AI adoption in healthcare delivery

- Lack of trust in AI solutions
- Bias in medical Al
- Lack of systematic implementation approach
- Compliance with regulation
- Lack of governance processes and maintenance and monitoring infrastructure







(b) Model Building and Implementation

Wu E, Wu K, Daneshjou R, Ouyang D, Ho DE, Zou J. How medical AI devices are evaluated: limitations and recommendations from an analysis of FDA approvals.

Suresh H, Guttag JV. A framework for understanding unintended consequences of machine learning. arXiv preprint arXiv:1901.10002. 2019 Dec 30;2(8):73.

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Ecosystem Partners



Federal Agencies





for Health Information Technology *Participating as a federal observer

U.S. Department of Veterans Affairs Veterans Health Administration Office of Discovery, Education and Affiliate Netwo

Health AI Partnership

Our mission: Empowering healthcare professionals to use AI effectively, safely, and equitably through community-informed up-to-date standards

Our values:

advance health equity

prioritize solutions that advance health equity and eliminate the AI digital divide

improve patient care

ensure that AI adoption is driven by patient care needs, not technical novelty

improve the workplace

surface socio-technical challenges in AI use and foster a positive work environment



build community

create safe spaces to share learnings and consult peers

Milestones of phase 1 (April 22 - August 23, 2023)

Standard AI Solution Procurement Milestones

- Best practices sourced from across the HAIP organizations
- Co-design workshops with IDEO.org
- Focused on AI solutions used for:
 - Diagnosis or treatment decisions for patients
 - Prioritization of patients for healthcare services _ (e.g., surgery scheduling, care management prioritization, ED triaging)





Health Equity Across the Al Lifecycle (HEAAL) Framework

Developed detailed procedures for healthcare organizations to follow for AI procurement

Developed to answer the question: "Our health system is considering adopting a new solution that uses AI; how do we assess the potential future impact on health inequities?"

Multi-stakeholder workshop featuring case studies, expert discussants, and framework developers

Case **Studies**





Crowded Ecosystem of Al Conveners

Organization	Description	Organization	Description		
Health AI Partnership	A multi-stakeholder collaborative who seeks to empower healthcare organizations to use AI safely, effectively, and equitably. Vision is to be the trust partner and up-to-date source of actionable guidance for healthcare	American Medical Informatics Association (AMIA)	A society for health informatics professionals that offers education, training, accreditation, and certifications.		
(HAIP)	professionals using AI.	Society for Imaging Informatics in Medicine (SIIM)	Healthcare professional organization for those interested in use of informatics in medical imaging.		
Coalition for Health Al	A community of academic health systems, organizations, and expert practitioners of artificial intelligence (AI) and data science.				
Valid Al	A collaborative community to advance generative AI in a responsible manner to improve health care and research	National Academies of Medicine AI Code of	Aimed at providing a guiding framework to ensure that AI algorithms and their application in health, health care, and biomedical science perform accurately,		
HIMSS (Healthcare			safely, reliably, and ethically in the service of better health for all.		
Information and Management Systems Society)	ecosystem. This society offers educational resources such as course materials, guides, webinars, and certifications on a range of health information and technology subjects.	Digital Health Collaborative	The Digital Health Collaborative is a group of leading healthcare and consumer organizations that share a commitment to "raising the bar" for evidence and value in digital health technology.		
HLTH	Community for innovators in the healthcare ecosystem. Has a heavy industry focus. Hosts conferences and creates digital content like webinars, podcasts, and blogs.	The Al Alliance	A community of technology creators, developers and adopters collaborating to		
	An international multi-stakeholder membership-based advocacy group organized to influence regulatory principles for development and implementation of AI in healthcare.		advance safe, responsible AI rooted in open innovation. Through collaboration, TRAIN members will help improve the quality and		
AI Healthcare Coalition	An industry advocacy group to influence on health care AI policy and law.		trustworthiness of AI by: - Sharing best practices related to the use of AI in healthcare settings		
Healthcare Products Collaborative	Promotes discussion and innovation in the healthcare products community, bringing together regulators, professionals, academics, and thought leaders to tackle industry challenges.		 Enabling registration of AI used for clinical care or clinical operations Providing tools to enable measurement of outcomes associated with the implementation of AI 		
Connected Health Initiative	A multi stakeholder coalition that advocates for policies and laws related to Al in healthcare. They educate regulators and lawmakers and publish white papers that define industry best practices.	Trustworthy & Responsible AI Network (TRAIN)	- Facilitating the development of a federated national AI outcomes registry for organizations to share among themselves.		
The AI Collaborative	A peer learning and consulting services to clinical and operational executives who oversee their organization's investment in AI tools for healthcare.	Collaborative Community on Ophthalmologic Imaging	A collaborative of academic institutions, government agencies, private businesses, and professional organizations dedicated to establishing standards of practice for innovative ophthalmic imaging.		
KLAS Research	A consulting services that evaluates digital products by aggregating and synthesizing feedback about vendor products.		The Center for AI Policy (CAIP) is a nonpartisan research organization dedicated to mitigating the catastrophic risks of AI through policy development and		
Machine Learning for Healthcare	Academic publishing and dissemination of scientific work	Center for AI Policy (CAIP)	advocacy. The Center' firmly believes that, if managed carefully and prudently by the right		
Association for Health Learning and Inference	Academic publishing and dissemination of scientific work	Center for Public Sector A.I.	leaders, technology like generative AI can significantly improve government agencies' ability to serve the public.		

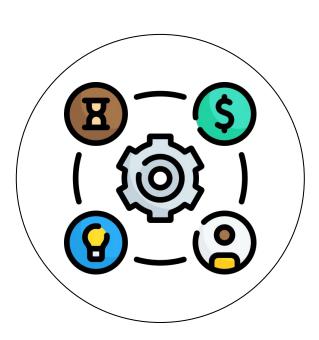


Crowded Ecosystem of Al Conveners

rganization	Description	Organization	Description			
	A multi-stakeholder collaborative who seeks to empower healthcare organizations to use AL safely, effectively, and equitably. Vision is to be the trust			ucation, training,		
ealth AI Partnership IAIP)	Organizations vary significantly	ganizations vary significantly across:				
oalition for Health Al	 Types of content produced (e.g. 	anuscripts, actionable				
id AI //SS (Healthcare	guidance, technical standards)		orithms and their form accurately, all.			
ormation and anagement Systems	 Frequency of content updates 			are and consumer r evidence and value		
ciety)	- Types of convenings (e.g., publ	, closed-door workshops)				
TH	- Primary target audience (e.g., a	- /	s collaborating to			
liance for AI in Healtho	- Business model (e.g., pay for c	events, pay for	quality and			
Healthcare Coalition	certification)			settings perations		
althcare Products aborative	- Organization structure (e.g., housed within AMCs, 501(c)3, 501(c)6,					
	for-profit companies)			omes registry for		
nnected Health Initiat AI Collaborative Jance + The Academ	- Level of industry participation		s, private ıblishing standards o			
AS Research	 Focus on government advocacy 	У		anization dedicated		
achine Learning for ealthcare	Academic publishing and dissemination of scientific work Academic publishing and publishing and publishing academic publishing academ					
ssociation for Health earning and Inference	Academic publishing and dissemination of scientific work	Center for Public Sector A.		ove government		

Differentiators of HAIP





Voice of healthcare organizations

Support high- and low-resource environments





Team of clinical, technical, operational, strategic, and regulatory stakeholders



Provider of technical assistance for AI implementation

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Building "practical" standards for AI adoption



Design research

Design prototype of the AI adoption standards that health system leaders find immediately useful in practice Understand the current and aspirational state of AI adoption in healthcare organizations and surface content to be included in the standards

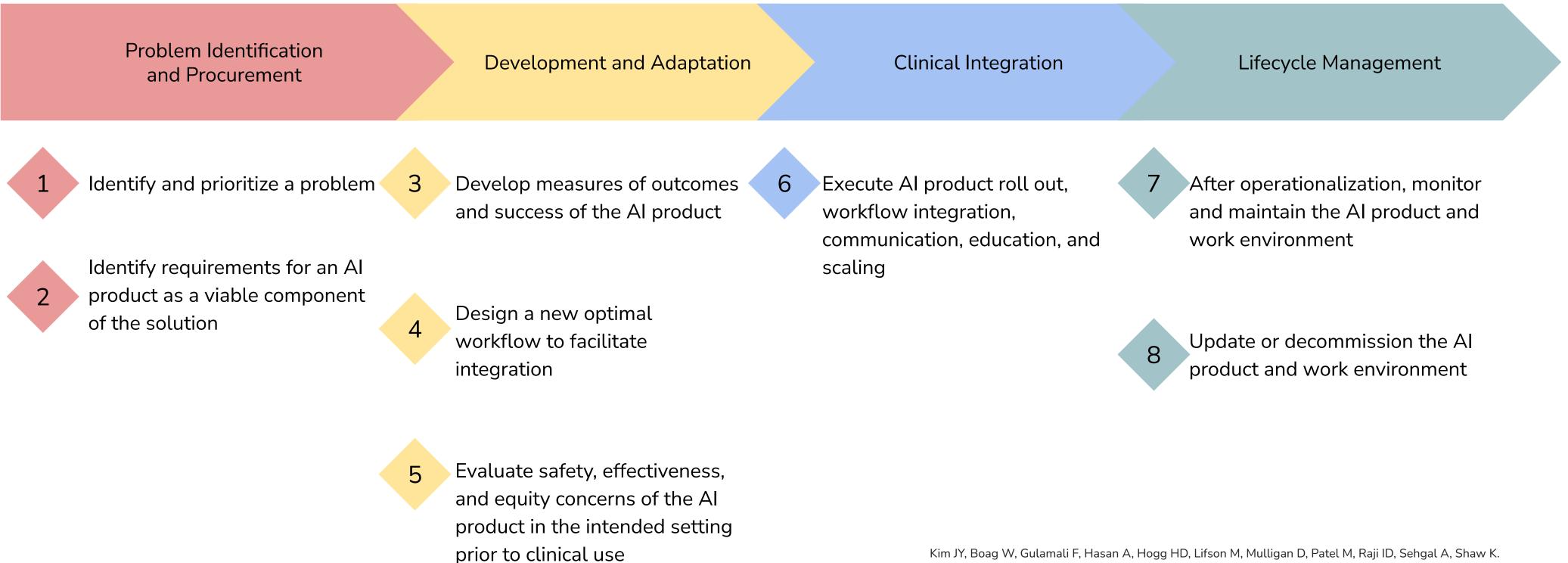




Qualitative research

Qualitative research

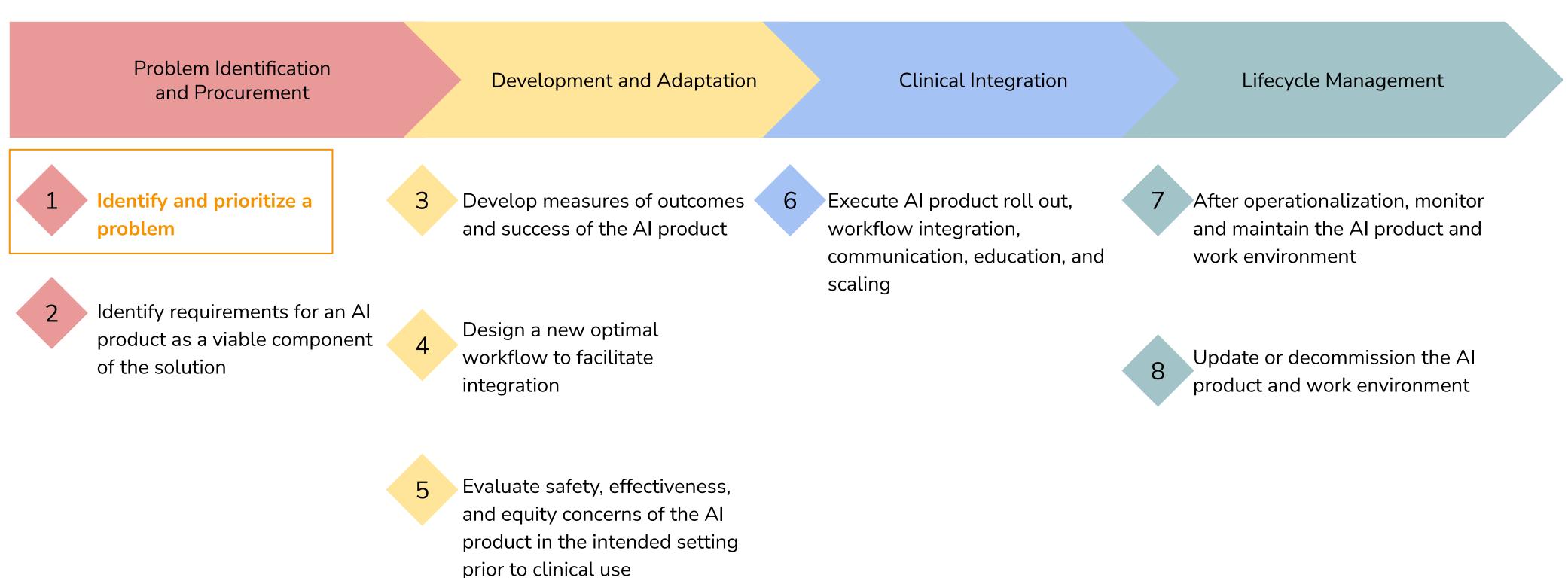
• **Results**: 8 key decision points in the AI adoption process





Kim JY, Boag W, Gulamali F, Hasan A, Hogg HD, Lifson M, Mulligan D, Patel M, Raji ID, Sehgal A, Shaw K. Organizational Governance of Emerging Technologies: AI Adoption in Healthcare. InProceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency 2023 Jun 12 (pp. 1396-1417). 36







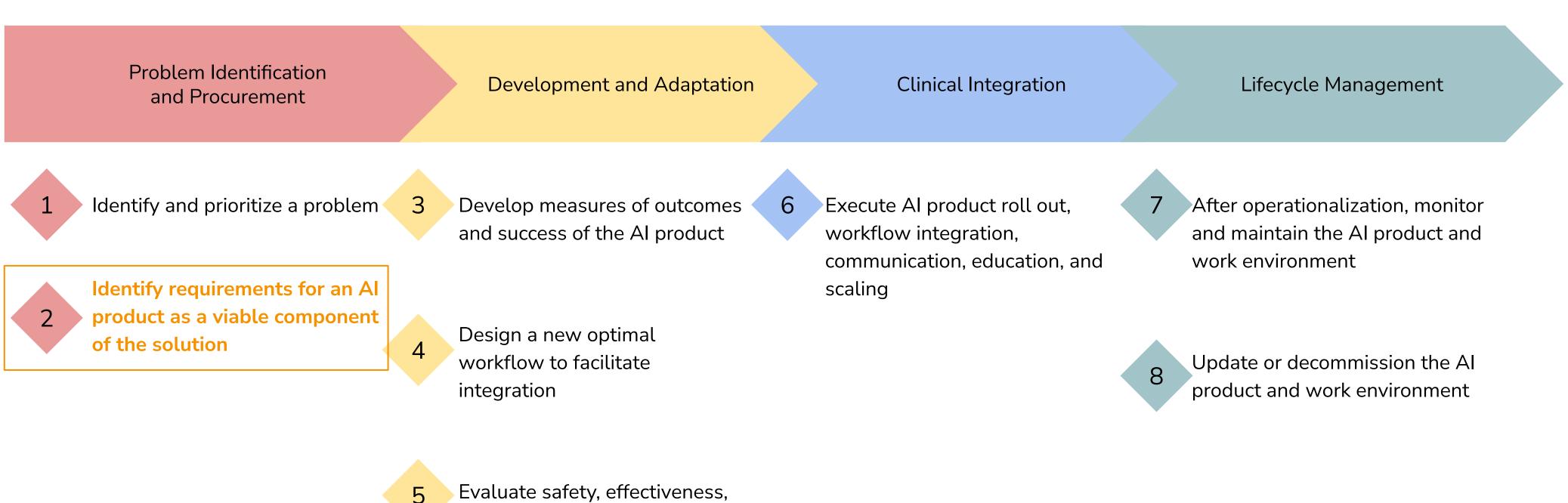
Create alignment with frontline staff and organizational leaders throughout project selection

	Strategic Priorities	Proposal Solicitation	Project Selection	Scoping	Solution Development	Implementation & Evaluation
C-Suite	Specify 4-5 organizational innovation priorities	Publicize RFA	Rate oral pitches to select ~10 projects			Evaluate and determine impact and sustainability plans
Clinical and Operational Leaders (control resources)		Publicize RFA and work with front-line staff on proposal	Provide written reviews to select ~20 projects for oral pitches	Define problem, solution, stakeholders,	Design and develop	Define operationalizati on and dissemination,
Front-Line Staff		Iterate on proposal with buy-in from clinical and operational leaders		metrics, and measures	solution with DIHI	including communication and training

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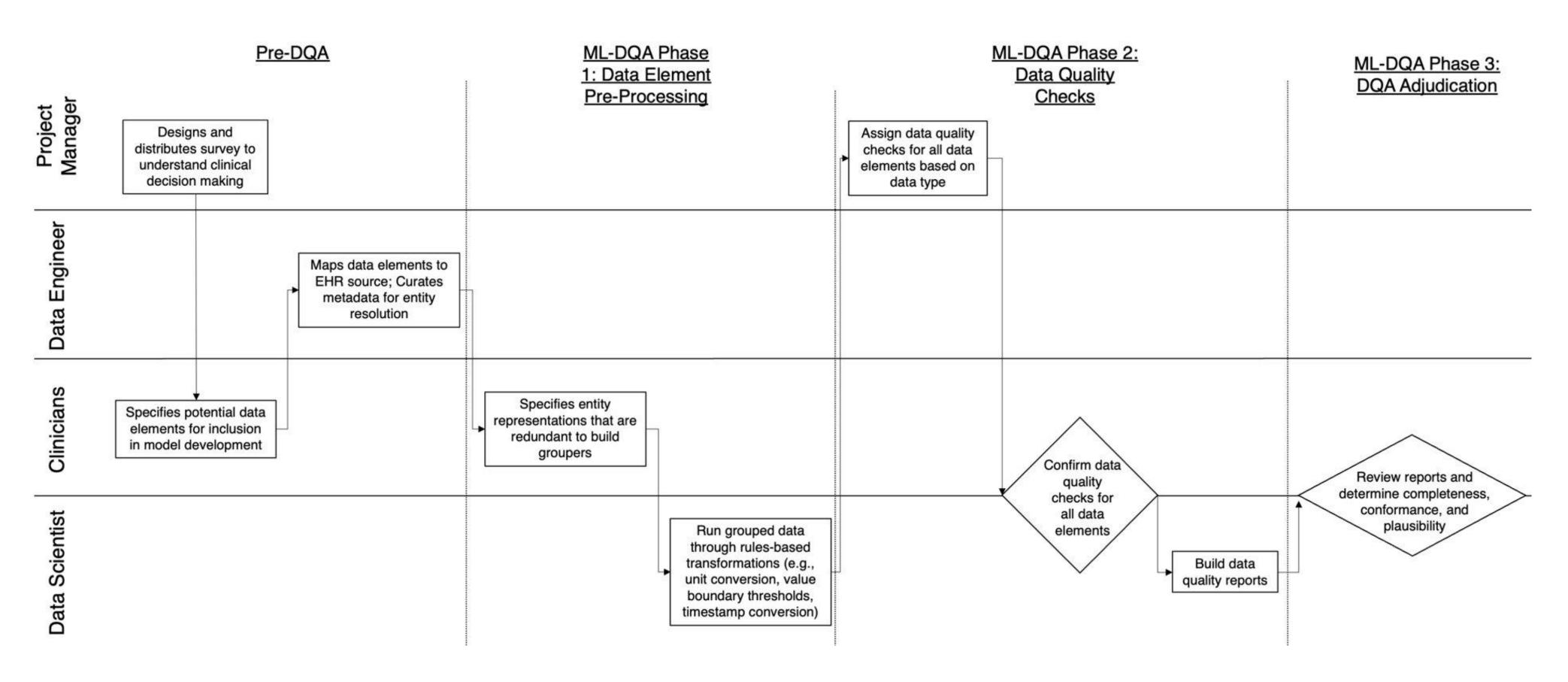
and equity concerns of the AI

prior to clinical use

product in the intended setting



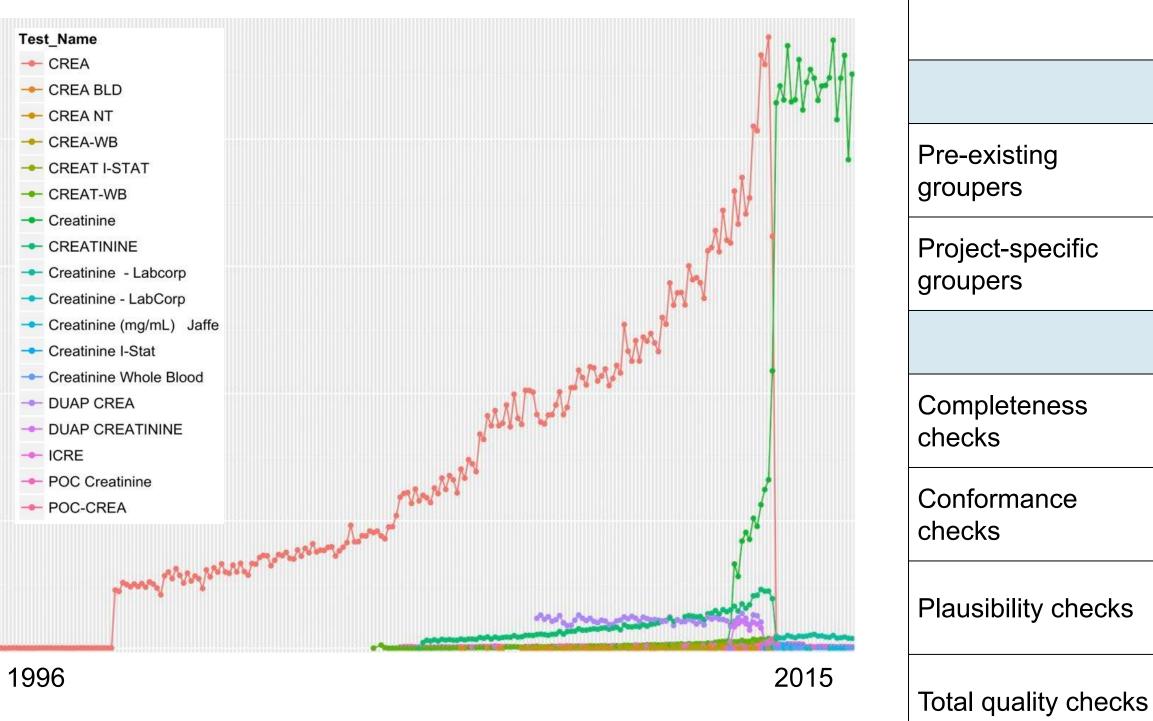
Conduct data quality assurance (DQA) and create groupers





Conduct data quality assurance (DQA) and create groupers

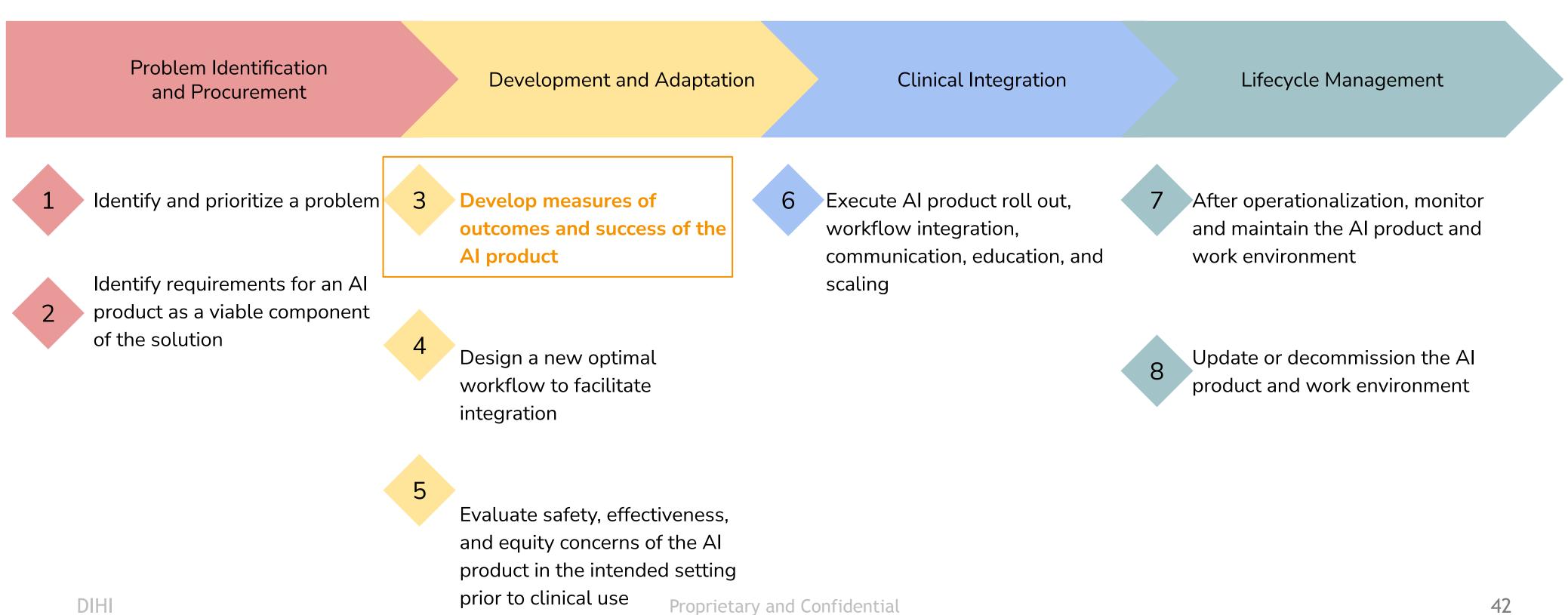
Which Creatinine?





	Pediatric Sepsis Prediction	Immune-Related Adverse Event Prediction	Maternal Morbidity and Mortality Prediction			
	Phase I: Data Eleme	ent Pre-Processing				
	108	39	310			
	73	41	12			
	Phase II: ML-DQA Checks					
	144	508	404			
	122	225	69			
	123	301	404			
S	389	1,034	877			

Decision point 3





Define categories of measures

Category	Definition
Model performance	Effectiveness, accuracy, and reliability of the Al model or algorithm in fulfilling its intended tasks within the clinical or healthcare context.
Software performance	Efficiency and responsiveness of processing tasks, delivering results, and overall performance of the software components and its interactions.
Clinical effectiveness	Assessment of impact of product use on healthcare outcomes.
Usability	Quality of users' interactions with the Al-based medical software.
Safety and security	Safe and secure operating software, evaluating harm to patients and protection against unauthorized access, data breaches, and cyber threats.
Business	Business objectives and outcomes

Y	
2	

Example Metrics
Sensitivity (recall, true positive rate), Specificity (true negative rate), Area Under the ROC Curve (AUC-ROC), F1 Score, Precision (positive predictive value).
Inference time, throughput, model latency, response time, resource utilization, scalability.
Mortality rate, intensive care unit requirement, complication rate
Clinician satisfaction, user error rates, ease of use.
Number of identified safety risks and mitigations, adherence to cybersecurity standards, detection of adversarial attacks, incident response time.

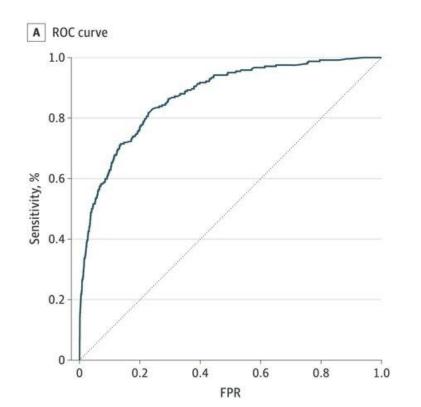
Reduction in diagnostic time, cost savings.

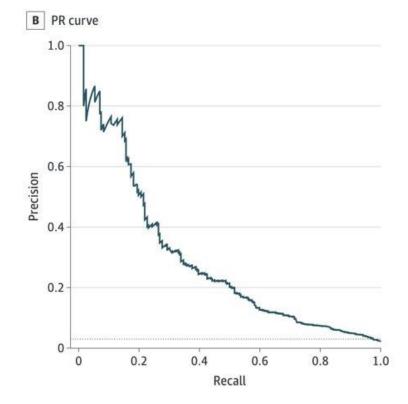
Evaluate model performance against defined measures

Mortality model performance measures

Table 2. Prediction Accuracy by Evaluation Method, Location, and Time

Evaluation Method	Location	Time	AUROC (95% CI)	AUPRC (95% CI)
Retrospective	Hospital A	2014-2015	0.87 (0.83-0.89)	0.29 (0.25-0.37)
Retrospective	Hospital A	2018	0.85 (0.83-0.87)	0.17 (0.13-0.22)
Retrospective	Hospital B	2018	0.89 (0.86-0.92)	0.22 (0.14-0.31)
Retrospective	Hospital C	2018	0.84 (0.80-0.89)	0.13 (0.08-0.21)
Prospective	Hospital A	2019	0.86 (0.83-0.90)	0.14 (0.09-0.21)



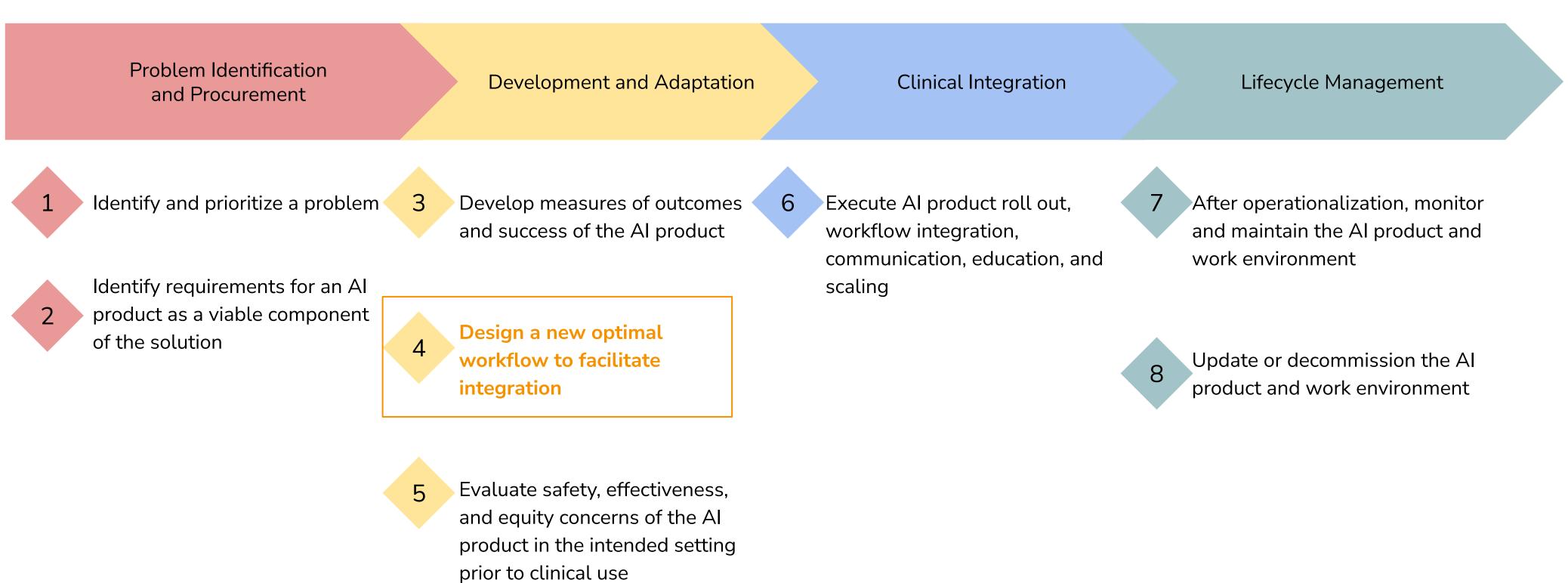


				Alerts, No./d	Alerts, No./d	
Threshold	Sensitivity	Specificity	PPV	Total	False	True
0.01	0.88	0.66	0.05	39.9	37.8	2.1
0.02	0.76	0.81	0.08	23.3	21.5	1.8
0.03	0.68	0.88	0.11	15.3	13.6	1.7
0.04	0.61	0.91	0.12	11.9	10.4	1.5
0.05	0.57	0.93	0.15	9.1	7.7	1.4
0.06	0.54	0.95	0.18	7.4	6.1	1.3
0.07	0.52	0.95	0.19	6.5	5.3	1.3
0.08	0.50	0.96	0.21	5.8	4.5	1.2
0.09	0.48	0.96	0.22	5.2	4.1	1.2
0.10	0.44	0.97	0.22	4.8	3.7	1.1
0.11	0.43	0.97	0.24	4.4	3.4	1.0
0.12	0.41	0.97	0.24	4.1	3.1	1.0
0.13	0.39	0.98	0.26	3.7	2.7	1.0
0.14	0.39	0.98	0.27	3.5	2.6	0.9
0.15	0.36	0.98	0.27	3.2	2.3	0.9
0.16	0.35	0.98	0.28	3.1	2.2	0.9
0.17	0.34	0.98	0.30	2.8	2.0	0.8
0.18	0.33	0.98	0.32	2.6	1.7	0.8
0.19	0.31	0.99	0.32	2.4	1.6	0.8
0.20	0.29	0.99	0.33	2.2	1.5	0.7
0.21	0.28	0.99	0.33	2.0	1.4	0.7
0.22	0.28	0.99	0.35	1.9	1.3	0.7
0.23	0.27	0.99	0.36	1.8	1.2	0.7
0.24	0.26	0.99	0.38	1.7	1.1	0.6
0.25	0.26	0.99	0.41	1.5	0.9	0.6

Abbreviation: PPV, positive predictive value.

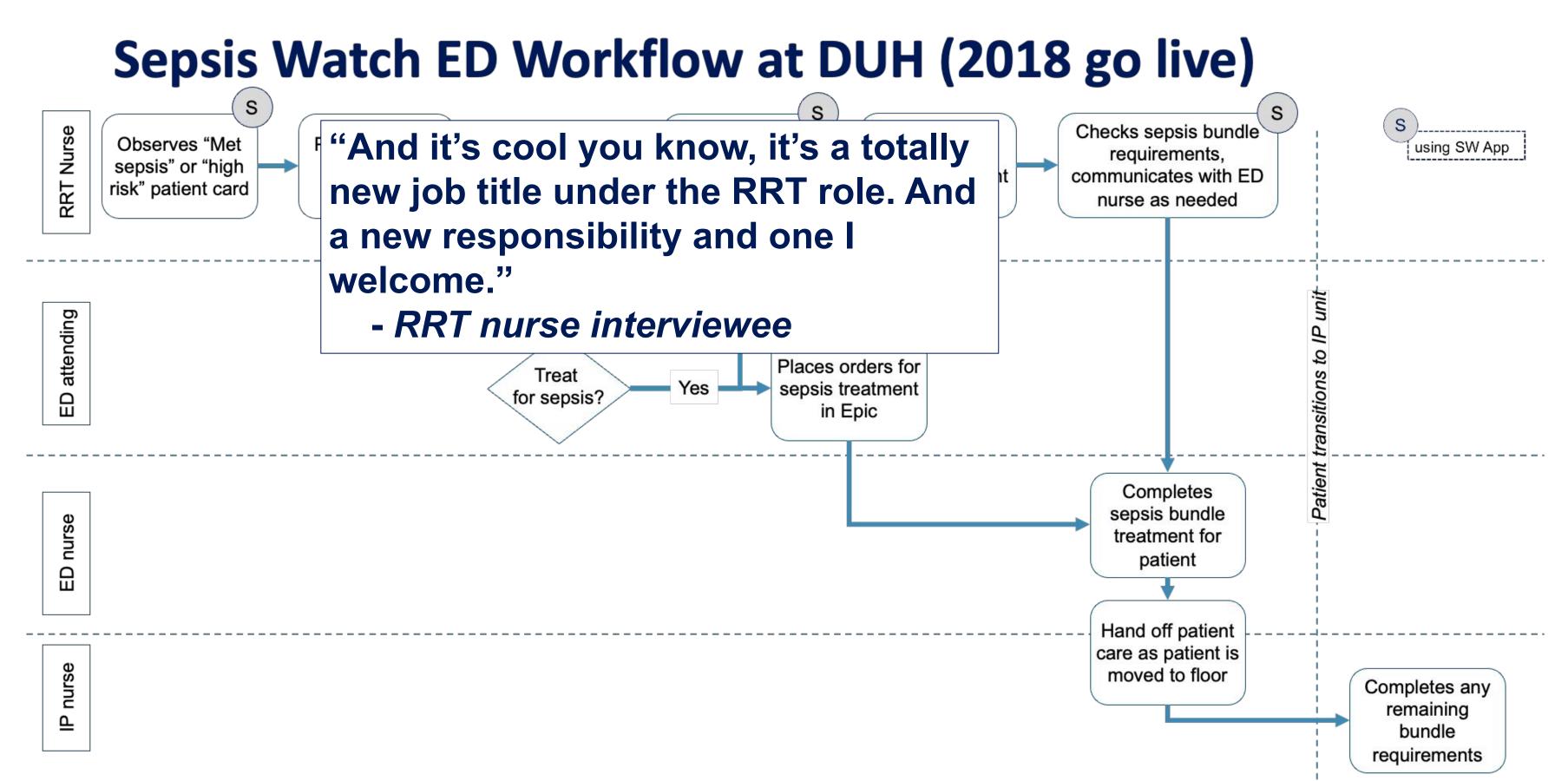
Number needed to evaluate = 1 / PPV

Decision point 4

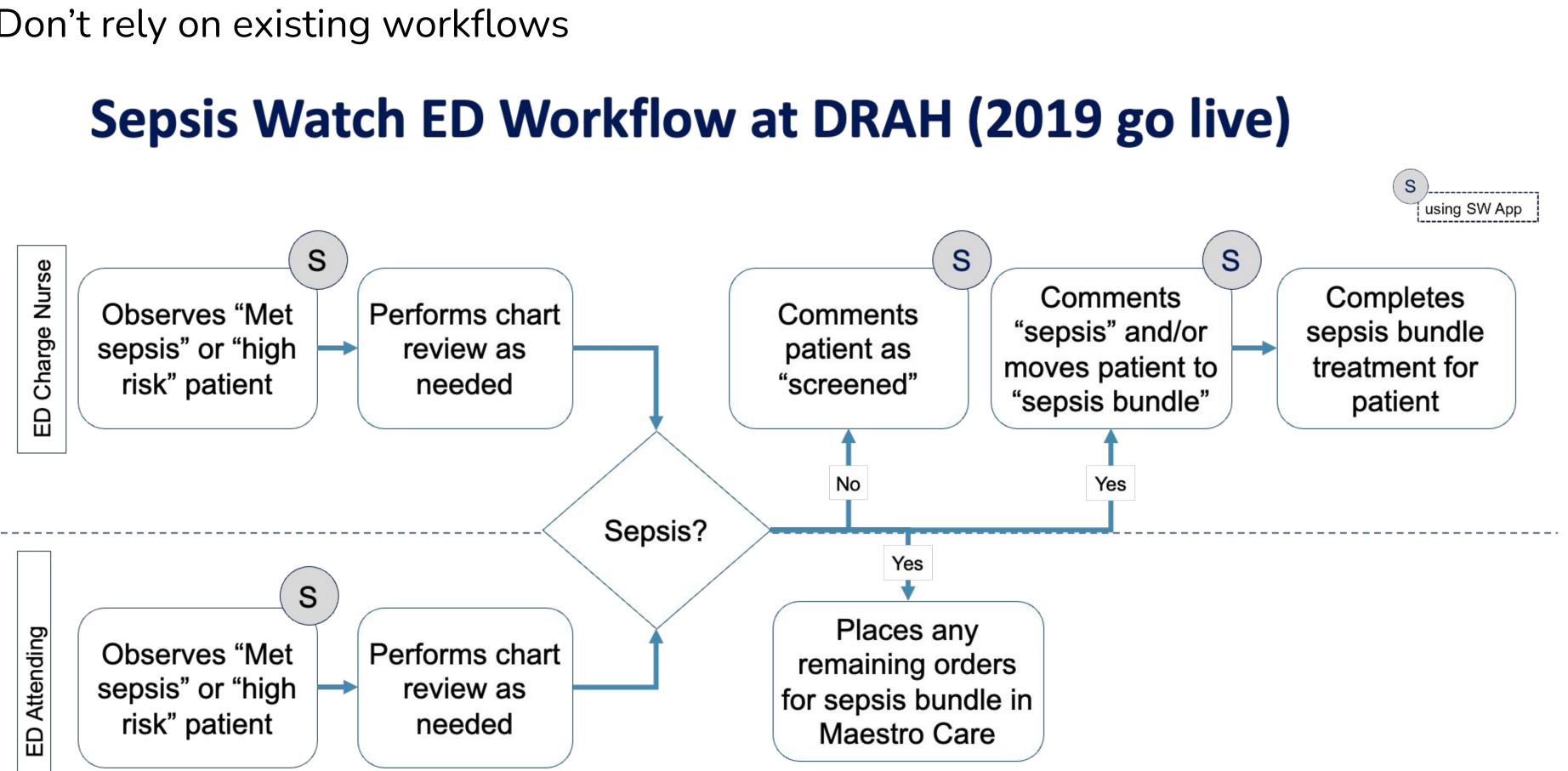




Adapt workflows, roles, and organization to solve problems: Don't rely on existing workflows

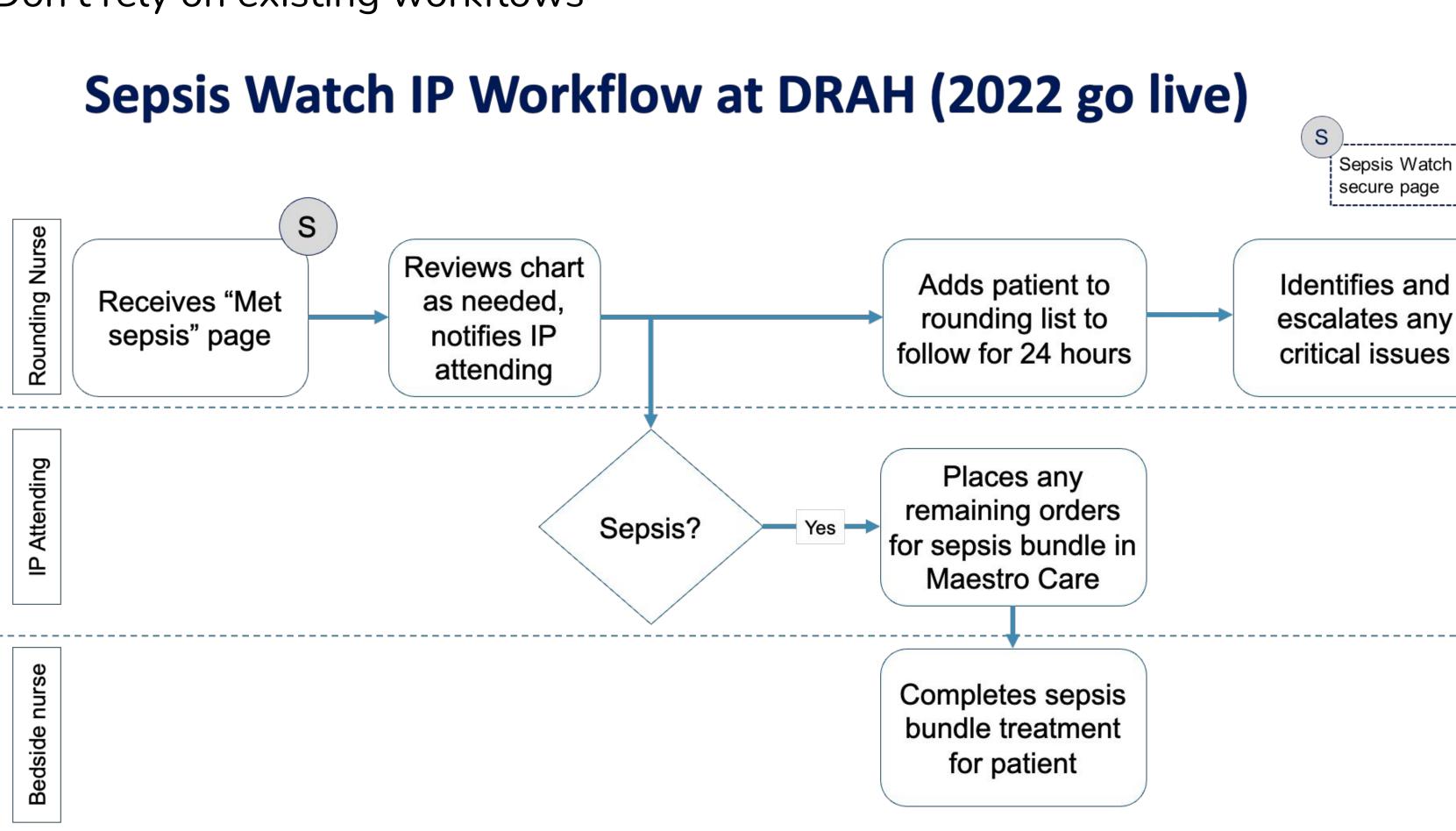


Adapt workflows, roles, and organization to solve problems: Don't rely on existing workflows

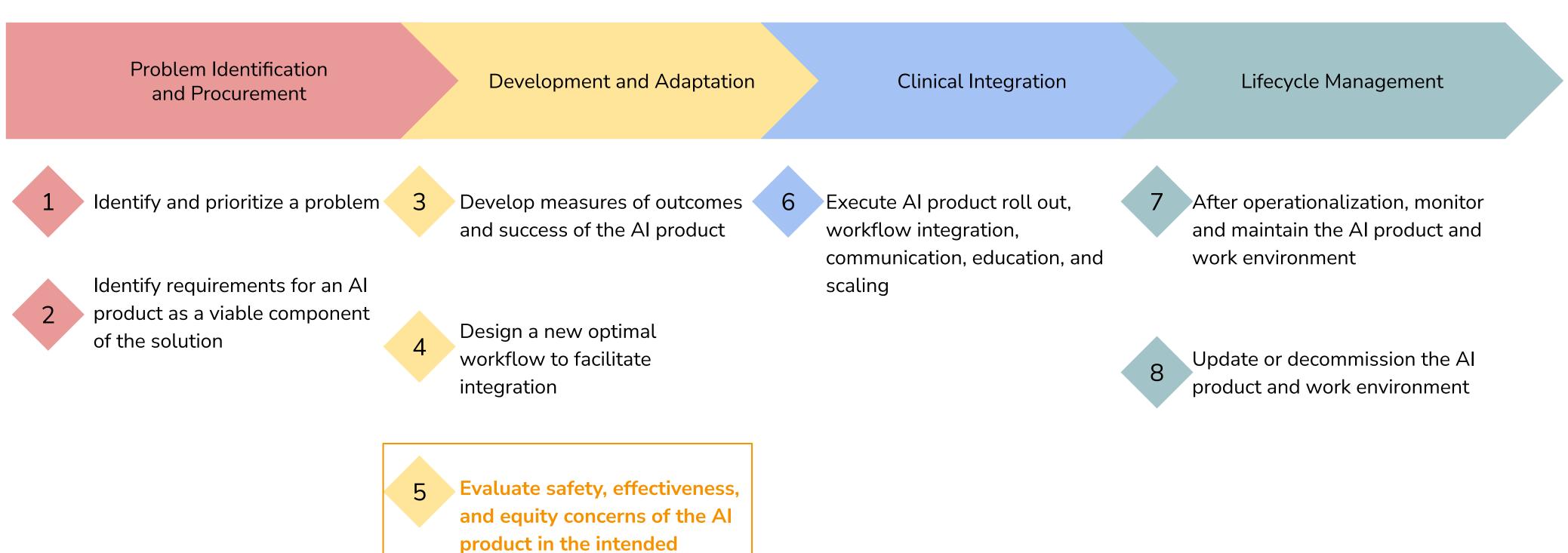




Adapt workflows, roles, and organization to solve problems: Don't rely on existing workflows



Decision point 5



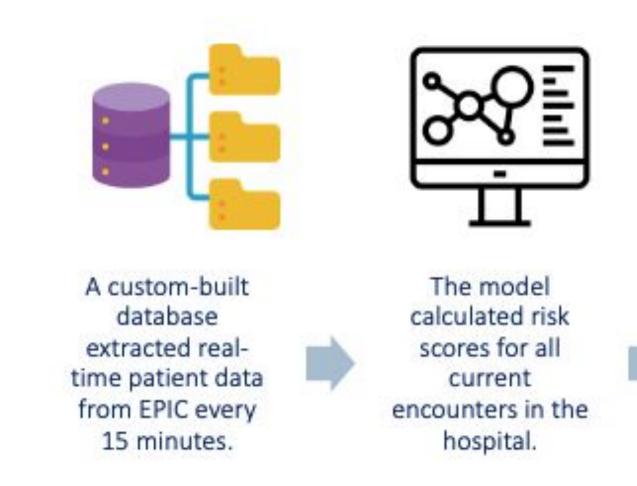
setting prior to clinical use



Pediatric sepsis prediction

- Outcome definition: Blood Culture \cap Antibiotics for 4 days \cap Acute organ dysfunction
- LSTM with 6-hour prediction window and 3-hour snooze
- Retrospective training set:
 - 17,491 unique encounters for children between 30 days old and 18 years old
 - Between November 1, 2016 December 31, 2020
- Temporal validation set:
 - 6,545 unique encounters for children between 30 days old and 18 years old
 - Between January 1, 2021 June 30, 2022





Silent Trial Design

	AUROC	AUPRC	PPV at 20% sensitivity (with 3hr snooze)	PPV at 50% sensitivity (with 3hr snooze)
Retrospective test set	0.816	0.483	0.769	0.612
Temporal validation	0.862	0.386	0.851	0.611









Alarm volumes were tracked and technical issues were resolved.

Silent trial results

- Model ran on 1,475 unique encounters over 2 months
- Model generated 30 alarms per day >> 2 alarms per day expected
- Model fired alarm on almost all patients in ED within first hour of arrival



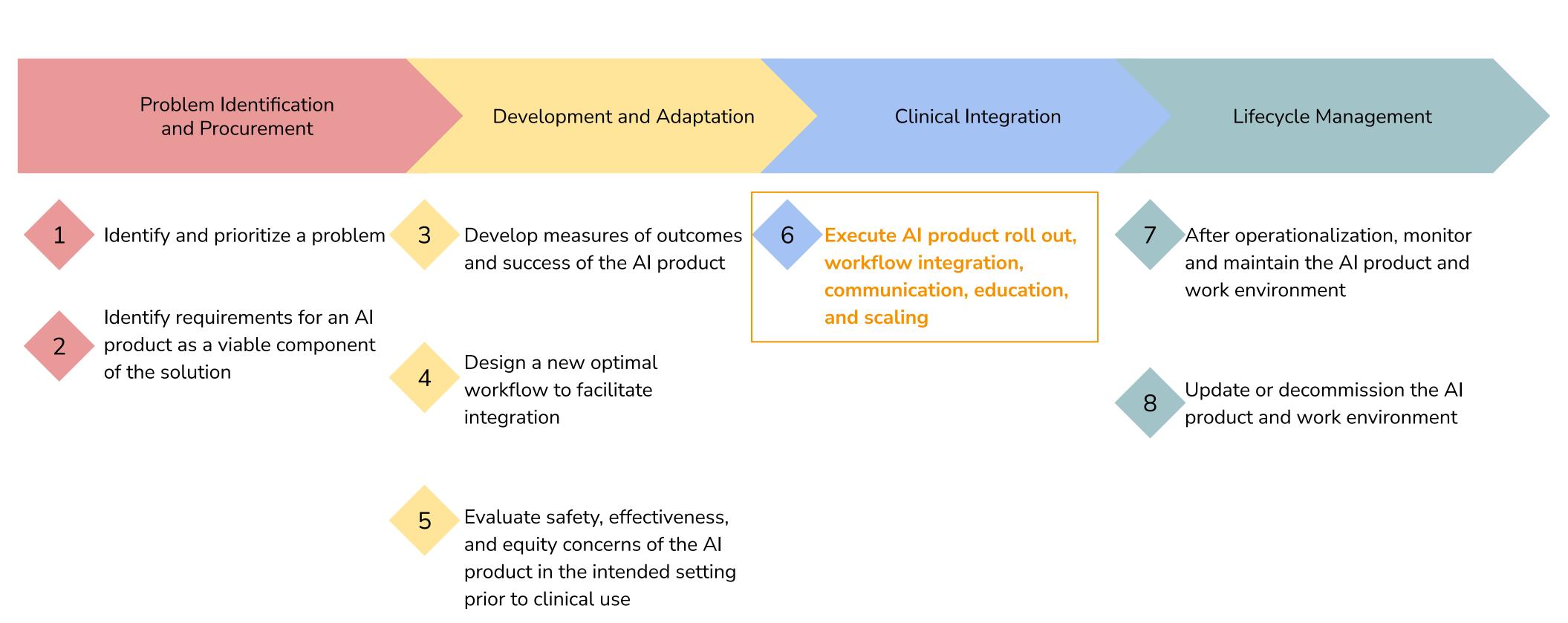
xpected

Retrained LSTM without layer normalization using the same hyperparameters

	AUROC	AUPRC
Retrospective test set (with layer normalization)	0.816	0.483
Temporal validation (with layer normalization)	0.862	0.386
Retrospective test set (without layer normalization)	0.782	0.01

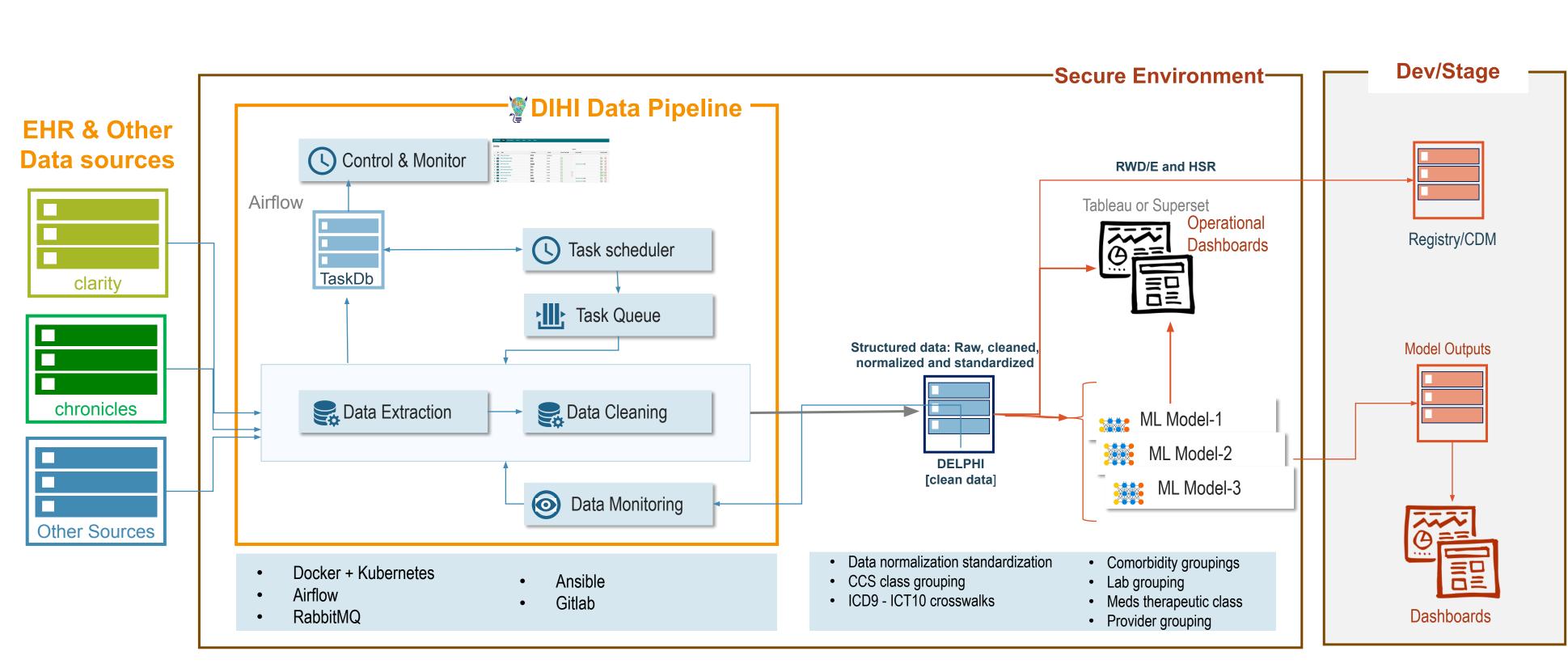


Decision point 6





Build modular infrastructure to support many projects: Flexible data pipeline technology infrastrastructure





Create model facts labels and share with end users and affected stakeholders

Comment | Open Access | Published: 23 March 2020

Presenting machine learning model information to clinical end users with model facts labels

Mark P. Sendak , Michael Gao, Nathan Brajer & Suresh Balu

npj Digital Medicine 3, Article number: 41 (2020) Cite this article

Warnings

Other information:

- Clinical impact evaluation: TBD

Proprietary and Confidential

Model Facts	Model name: Deep Sepsis	Locale: Duke University Hospital			
Approval Date: 09/22/2019	Last Update: 09/24	/2019. Version: 1.0			
Summary This model uses EHR input data collected from a patient's current inpatient encounter to estimate the probability that the patient will meet sepsis criteria within the next 4 hours. It was developed in 2016-2019 by the Duke Institute for Health Innovation. The model was licensed to Cohere Med in July 2019.					
Output	next 4 hours, see (1) for sepsis criteria of sepsis occurring in the next 4 hours of presenting to DUH ED and admitted every hour of a patient's encounter				

	Prevalence	AUC	PPV @ Sensitivity of 60%	Sensitivity @ PPV of 20%		
Local Retrospective	18.9%	0.88	0.14	0.50		
Local Temporal	6.4%	0.94	0.20	0.66		
Local Prospective	TBD	TBD	TBD	TBD		
External	TBD	TBD	TBD	TBD		

Uses and directions

- Operational use case(s): Every hour, data is pulled from the EHR to calculate risk of sepsis for every patient at the DUH ED. A rapid response team nurse reviews every high-risk patient with a physician in the ED to confirm whether or not to initiate treatment for sepsis.
- General use: This model is intended to be used to by clinicians to identify patients for further assessment for sepsis. The model is not a diagnostic for sepsis and is not meant to guide or drive clinical care. This model is intended to complement other pieces of patient information related to sepsis as well as a physical evaluation to determine the need for sepsis treatment.
- **Examples of appropriate decisions to support:** Patient X has a high risk of sepsis according to the model. A rapid response team nurse discusses the patient with the ED physician caring for the patient and they agree the patient does not require treatment for sepsis.
- Before using this model: Test the model retrospectively and prospectively on local data to confirm generalizability of the model to the local setting.
- Safety and efficacy evaluation: Analysis of data from clinical trial (NCT03655626) underway. Preliminary data shows rapid response team, nurse-driven workflow was effective at improving sepsis treatment bundle compliance.



5222 Accesses 9 Citations 73 Altmetric Metrics

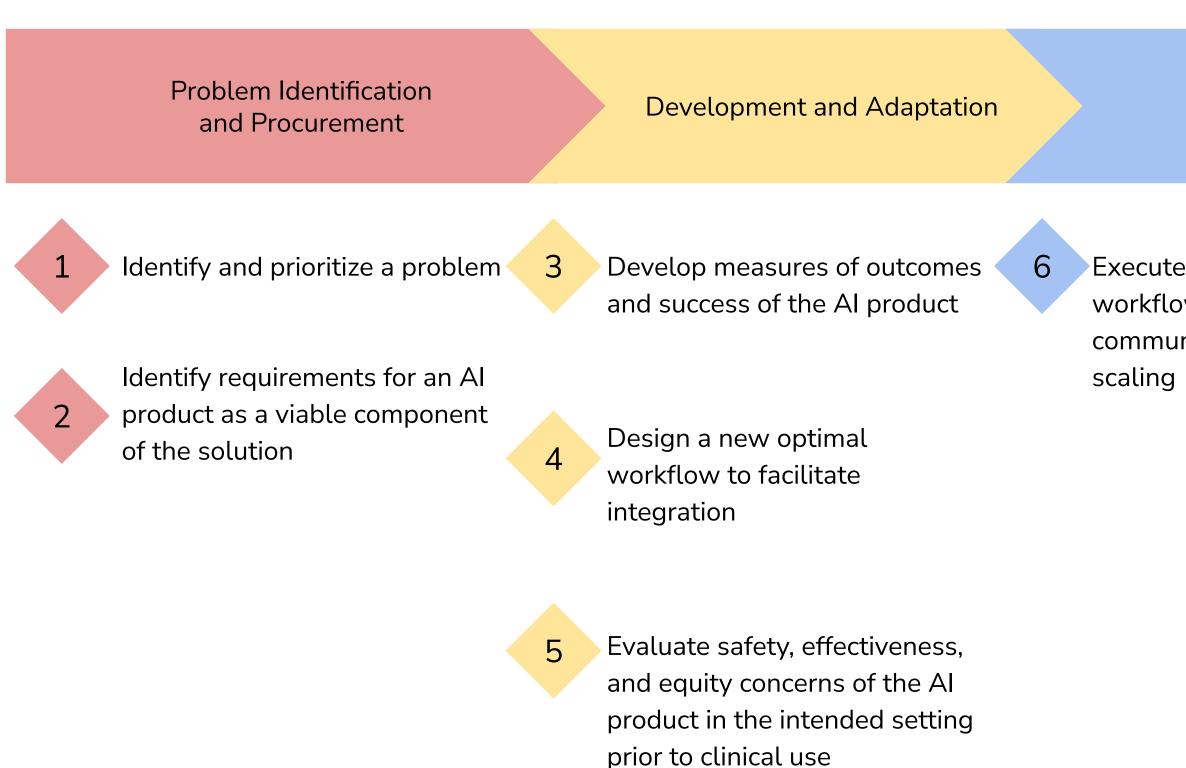
General warnings: This model was not trained or evaluated on patients receiving care in the ICU. Do not use this model in the ICU setting without further evaluation. This model was trained to identify the first episode of sepsis during an inpatient encounter. During long inpatient stays with multiple sepsis episodes, model accuracy needs to be further evaluated. The model is not interpretable and does not provide rationale for high risk scores. Clinical end users are expected to place model output in context with other clinical information to make final determination of diagnosis.

Examples of inappropriate decisions to support: This model may not be accurate outside of the target population, primarily adults in the non-ICU setting. This model is not a diagnostic and is not designed to guide clinical diagnosis and treatment for sepsis.

Discontinue use if: Clinical staff raise concerns about utility of the model for the indicated use case or large, systematic changes occur at the data level that necessitates re-training of the model.

Outcome Definition: https://doi.org/10.1101/648907 Related model: http://doi.org/10.1001/jama.2016.0288 Model development & validation: arxiv.org/abs/1708.05894 Model implementation: jmir.org/preprint/15182 Clinical trial: clinicaltrials.gov/ct2/show/NCT03655626 For inquiries and additional information: please email mark.sendak@duke.edu







Clinical IntegrationLifecycle ManagementExecute AI product roll out,
workflow integration,
communication, education, and
scaling7After operationalization,
monitor and maintain the AI
product and work environment

8

Update or decommission the AI product and work environment

Monitor AI system at DIHI

Effective monitoring of AI/ML solutions also requires multidisciplinary combination of technical and human capabilities, including expertise in engineering, data analysis, AI/ML, and clinical domain knowledge employed during the solution development phase.

Model Monitoring

- Data quality monitoring
 - Input data accurate, complete, and up-to-date
 - Entity/grouper monitoring
 - Continuous monitoring

•Performance comparison

- auroc, auprc wrt. training
- Analysis cadence: M/Q/Y

•Output drift monitoring

- Data distribution
- Category distribution

Solution Monitoring

- Outcome monitoring
 - Project specific measures
 - Bi-annual for most solutions

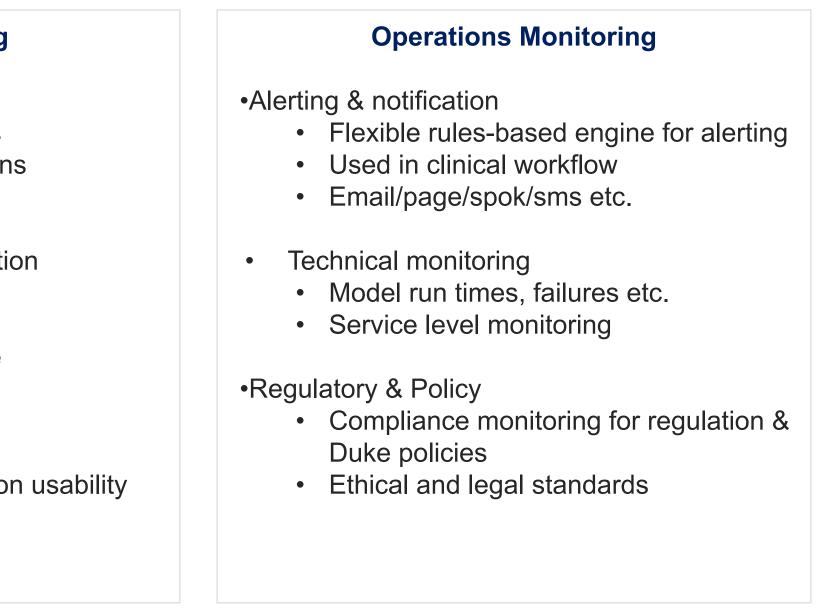
•Workflow changes

Observation / documentation

•Usage monitoring

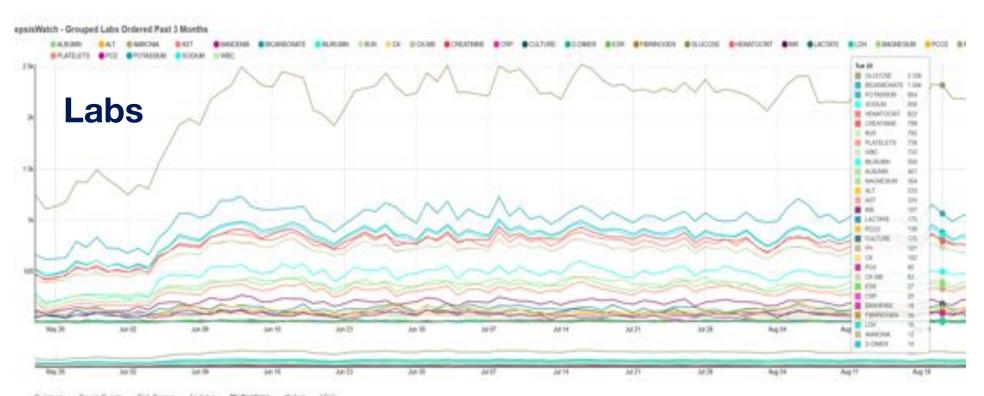
- UI tools/dashboard usage
- Secondary data analysis
- •User feedback
 - Survey for model & solution usability and refinements





Solution and Input Data Monitoring

Continuous monitoring to ensure safety and quality of data used in model inputs

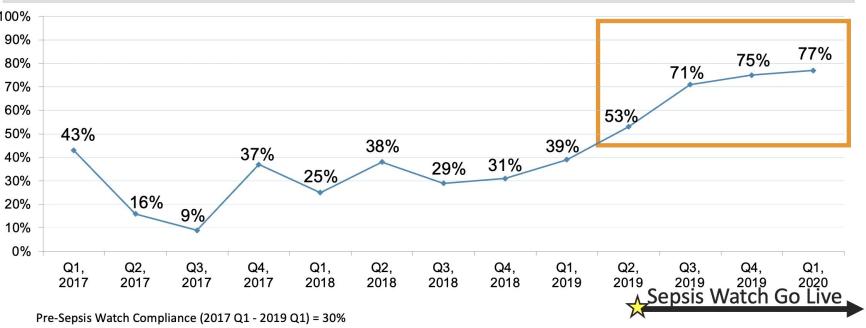


100% 90% 80% 70% 60% 50% 40% 30% 20% 10%

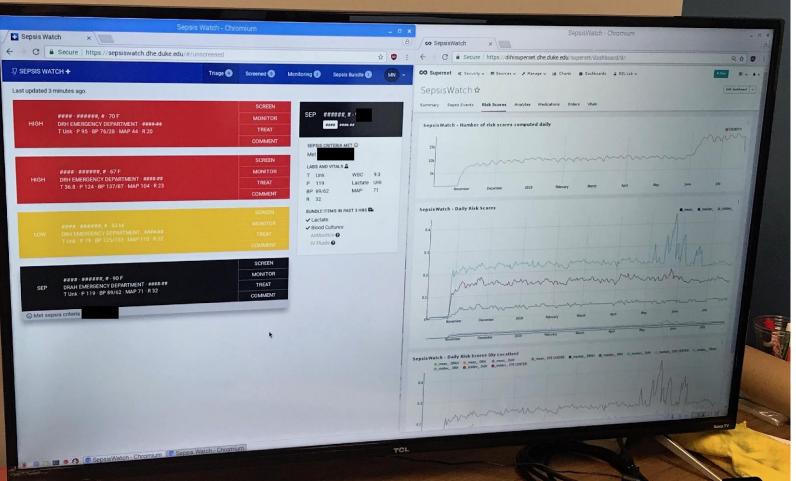




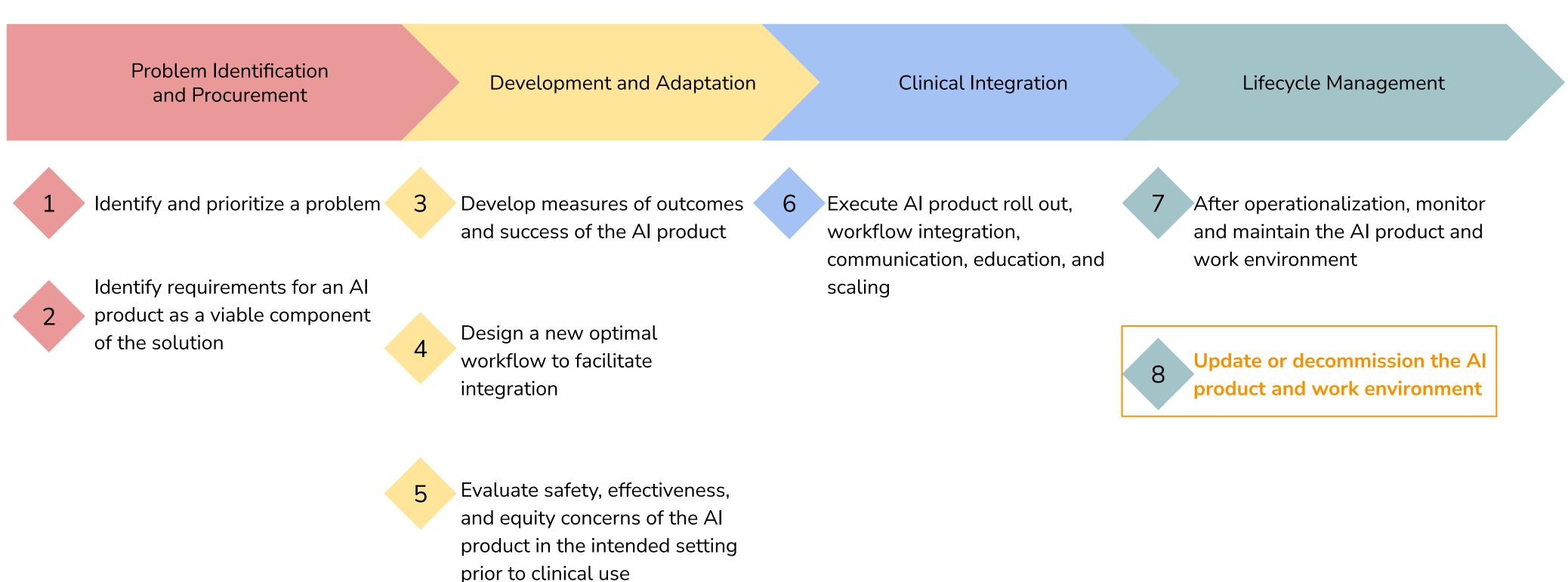
SEP-1 bundle compliance | Sepsis Watch model



Post-Sepsis Watch Compliance (2019 Q2 - 2020 Q1) = 70%



Decision point 8





Manage lifecycle of AI after clinical integration

Sepsis Watch post-integration lifecycle management

	Monitoring & Evaluation	Update	Operational Management
Event based	 Debug issues that arise (e.g., data endpoint unexpectedly goes down) 	 Customize the UI for different user groups Train new versions of the model for new clinical settings 	 Update user access Update reporting functionalities to support clinician management
Recurring	 Monitor technical elements of the model and source data in pipeline Monitor changes that affects work environment and use of model 	 Regularly scheduled maintenance (e.g., update groupers every 6 months) 	 Conduct bi-annual end user training to ensure baseline knowledge of Al system
Semi-Recurring	 Audit the solution for impact on clinical and operational outcomes and impact on work environment 	 Improve the UI (e.g., add comment feature, automatically check boxes) Scale to different use cases 	 Convene governance committee monthly Secure ongoing funding for AI system use
One-off	 Create channels for end users to report issues and provide user support services 	 Create process and criteria to scope responses to user requests 	 Determine ownership of model (e.g., clinical lead, technical lead)





Duke Institute for Health Innovation

Terminology

Big data and AI in healthcare

Health Al Partnership (HAIP)

Key Decision Points in Al Adoption

Organizational Governance of Al



2 mins

3 mins

2 mins

3 mins

15 mins

15 mins

Al Systems Monitoring Vs Governance

Monitoring

the Model

the solution

the operations

Purpose: To ensure the safety, effectiveness, and reliability of an AI applications in clinical settings.

Purpose: To establish broad oversight over the development, deployment, and general use of AI across the institution

Govern:

- Risk Mitigation
- legal, regulatory and ethical compliance,

Activities:

- use.

Activities:

Monitor:

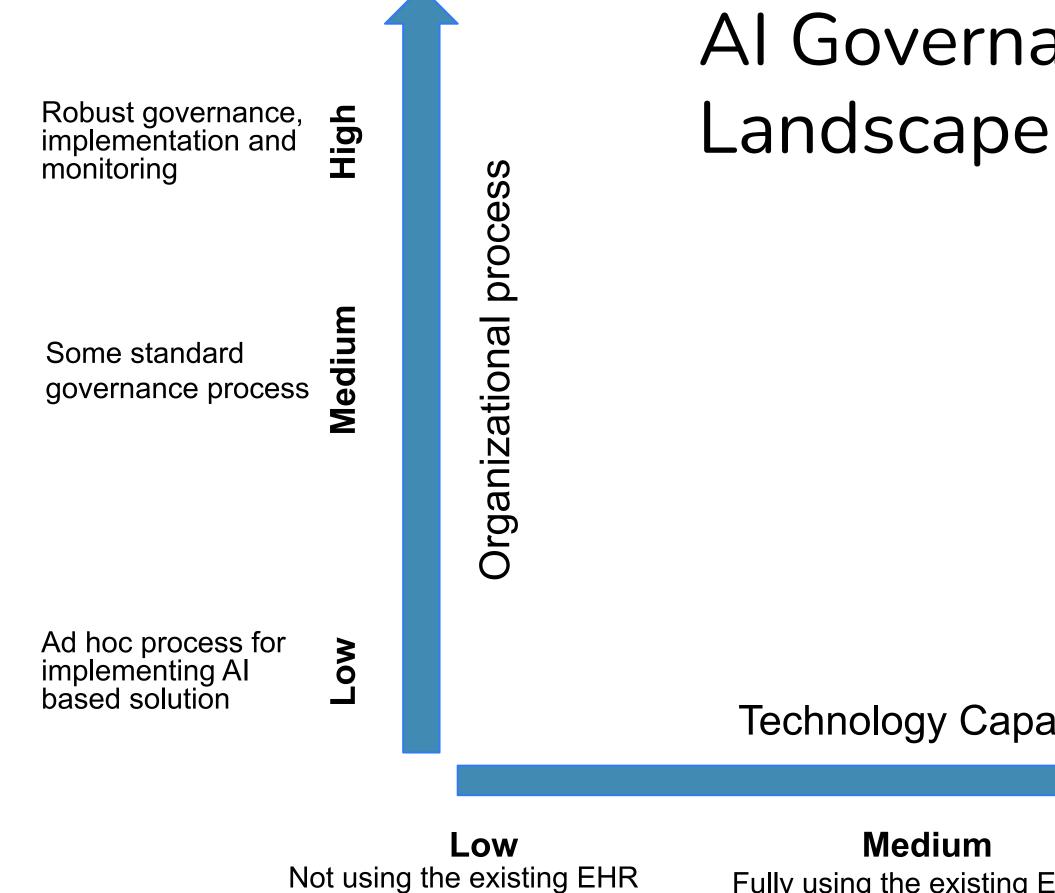
- Continuous data quality monitoring
- Continuous assessment of accuracy of the outcome
- Real-time tracking of AI performance against medical standards.

Governance

need and impacts of AI

Formulating policies and regulations for AI

• Promoting transparency and accountability in Al systems. Regular governance oversight • Addressing ethical concerns like bias, fairness, and human oversight.



capabilities

Fully using the existing EHR capabilities, implementing vendor based solutions

Proprietary and Confidential



Al Governance Maturity

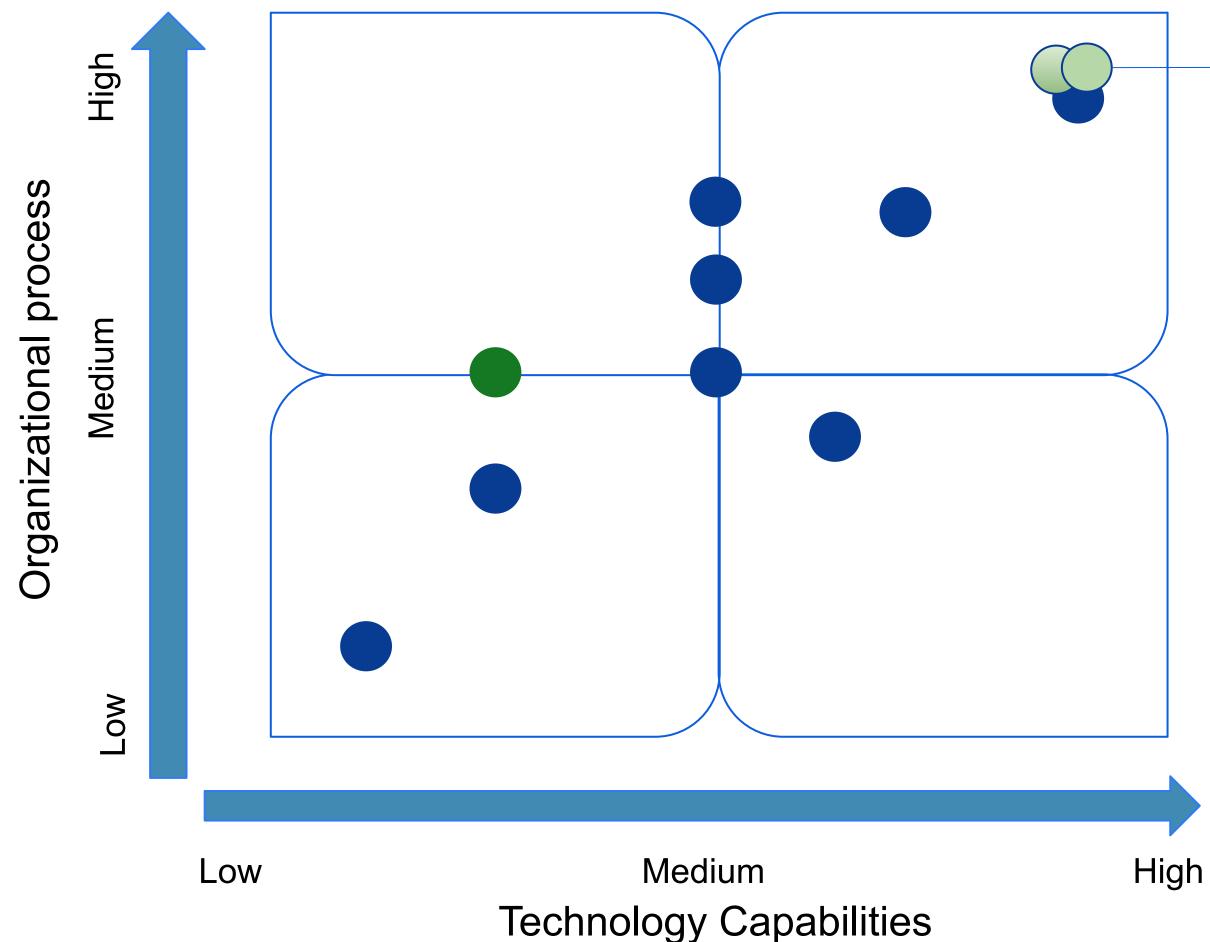
Technology Capabilities

High

Building custom infrastructure to enhance EHR capabilities and user interface

Duke Institute for Health Innovation

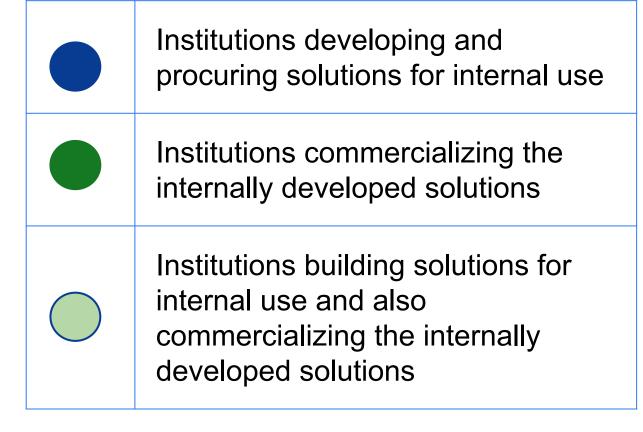
Al Governance Maturity Landscape



Proprietary and Confidential







Al Governance at Duke Health

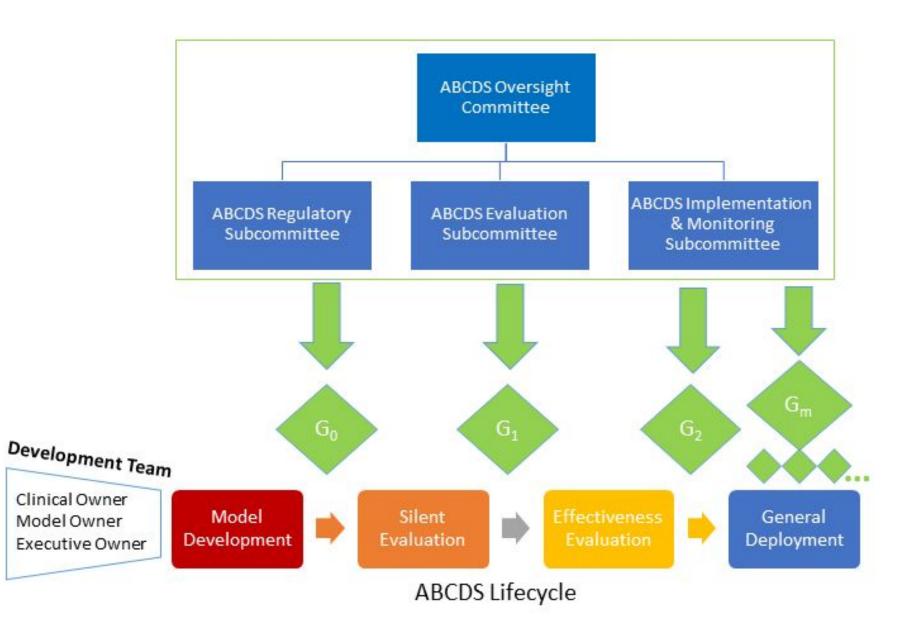
Algorithm-Based Clinical Decision Support (ABCDS) Oversight is a "people-process-technology" framework established in January, 2021 to provide governance, evaluation, and monitoring of algorithms used in clinical care and/or operations at Duke Health.

- The ABCDS lifecycle consists of 4 distinct phases with evaluation "checkpoints" placed at the transition points and at regular intervals in deployment.
- Readiness to proceed to the next ABCDS lifecycle phase is evaluated according to our 5 guiding principles:
 - **Transparency & Accountability** 1.
 - 2. Clinical Value & Safety
 - 3. Fairness & Equity
 - 4. Usability, Reliability & Adoption
 - 5. **Regulatory Compliance**

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Clinical Owner Model Owner Executive Owner





Definition of AI at Duke Health

A data-driven model (non-standard of care):

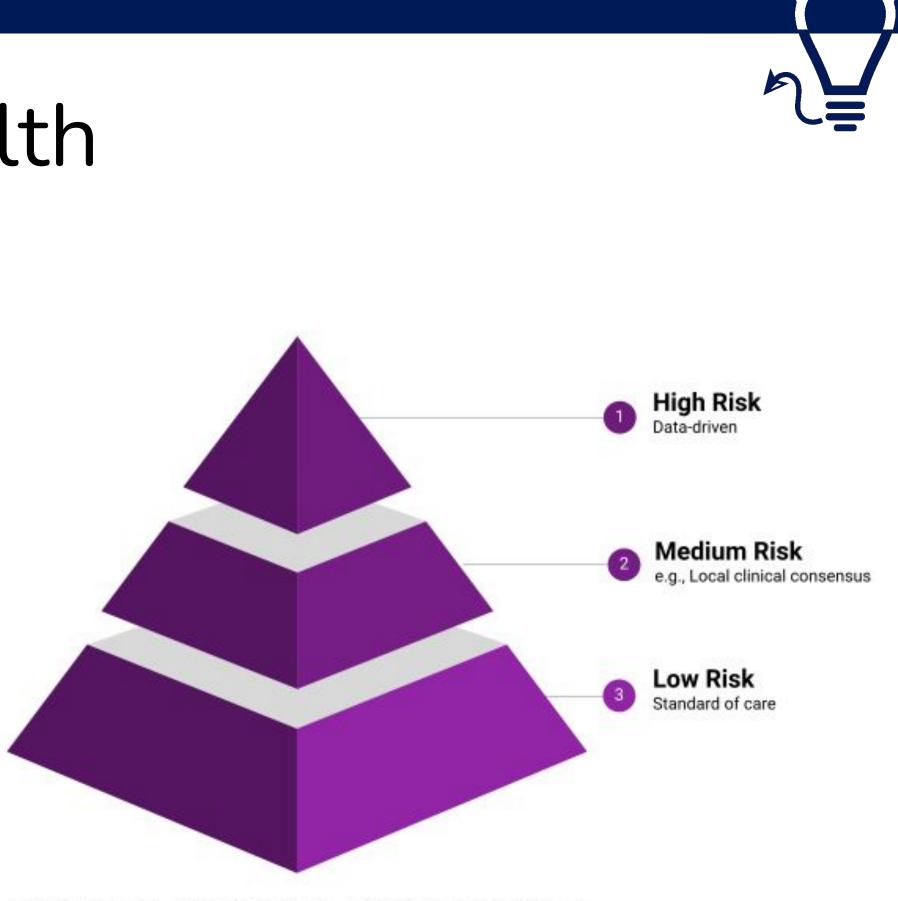
A model that builds relationships between input and output data using statistical/machine learning techniques.

A clinical consensus-based (knowledge-based) model: A formula or set of rules that were derived based on clinical acumen and consensus, the literature, and/or expert recommendations. These algorithms provide the same results on the same inputs.

A 'standard of care' tool or model:

A tool or model used to guide standard-of-care and would be supported by evidence in the medical literature, recommended by medical societies, or incorporated into clinical practice guidelines.

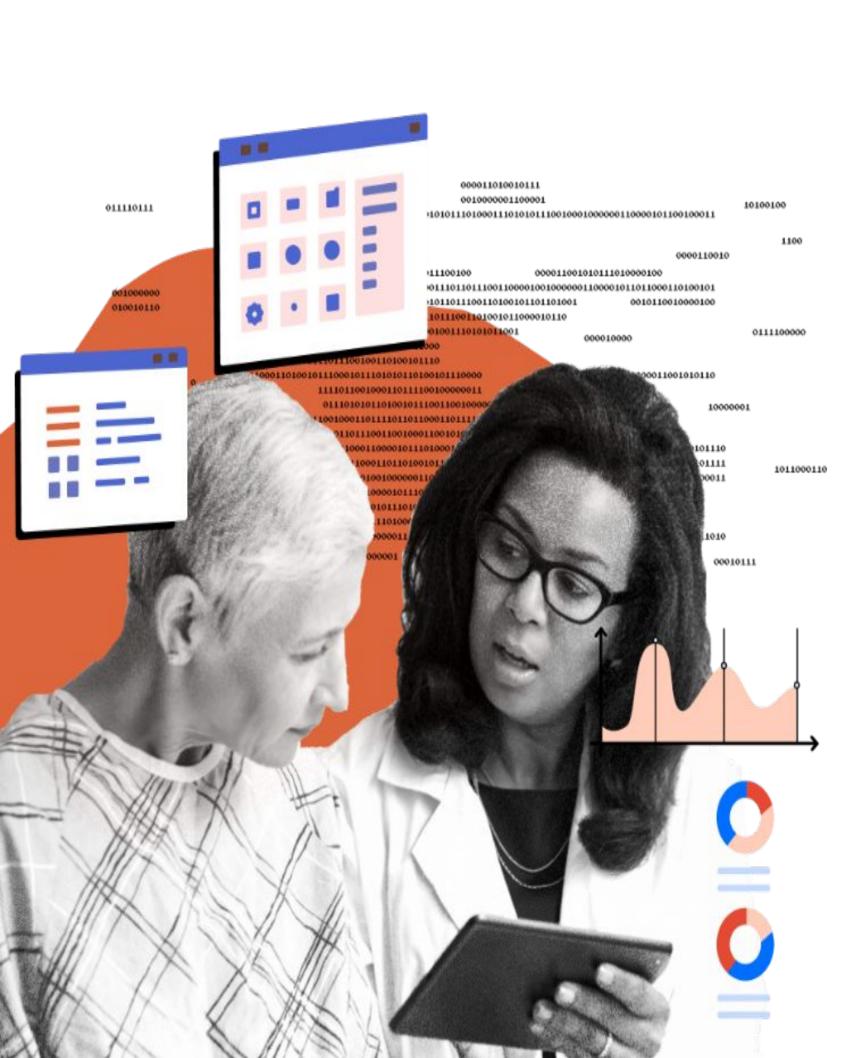
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ABCDS Tool = Algorithm(s) + Interface Algorithms





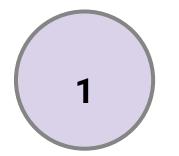


Duke Institute for Health Innovation



Customizing **Al Governance Practices** at for an Institution

Method



Interview and Discovery

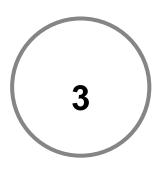
- Interviewed 12 stakeholders
- To analyze the current state of AI governance
- To surface needs for future AI governance

Algorithm Journey Mapping

2

- Interviewed the site lead
- To identify key stakeholders for future AI governance
- To map out process for future Al governance





Finalize Outputs and Share Back

- Finalize future AI governance process
- Help implementing the new lacksquareAl governance in practice



Status Quo Governance process

Procurement

 Problems are identified across the organization. Feasibility of adoption is assessed. No clear evidence-based reason for AI adoption No sufficient time and transparency for assessing a problem and a solution Lack of relevant key stakeholders' involvement in the procurement process 	 Stron Active Active new Heave Ad heave
 <u>Clinical Integration</u> <u>Established communication channels</u> Heavily dependent on the vendor (variability) No sufficient education about the AI solution provided to those affected by the solution adoption 	 Estal softv No sy users Insuf No sy

Gaps and opportunities for improvement

Development or Adaptation

- ong data infrastructure and capabilities tive engagement of a clinical team in designing a w workflow
- avily dependent on the vendor (variability)
- hoc sessions to design and test UI/UX with end ers
- nited discussion of success measures for projects ck of internal validation and evaluation
- systematic decision process for rollout

Lifecycle Management

- ablished end user support channels for EHR
- ftware
- systematic approach to gather feedback from end ers
- ufficient monitoring
- systematic approach for updating or
- decommissioning the AI solution or its ecosystem

Interview Findings

"A lot of times, the problem is not clear. We're already jumping to the solution and going out to look for something or purchase something without even understanding the problem."

- Technical Stakeholder

"As a clinician, there needs to be value that feels safe. There needs to be proper understanding of what is the role of the tool and what is my role and what's affecting who and what degree."

- Operational Stakeholder

"We work in silos."

- Operational Stakeholder

Procurement

Development

"Why are you selecting this when there's knowledge that there's three or four others? We want to know their vetting process. Did you look at all the different tools? What was your decision making process for selecting this one?"

- Operational Stakeholder

"The project team has been running the whole thing. Ideally, maybe it should be the clinical operations stakeholders to define a clinical problem who define what the benchmark for success should be. And the project team is more about execution, but that's not how it played out in this instance."



The presentation of performance metrics for all these algorithms by the vendors is completely different. There's no way to standardize them. It's very difficult. So we need to do this evaluation in house."

- Technical Stakeholder

Integration

Lifecycle Management

"Performance dropped by 5%. What should we do? No, that doesn't exist today."

- Clinical Stakeholder

Recommendations

3

1) People

- Define roles and responsibilities of key stakeholders who are responsible for implementing unified Al governance.
- Create education and training programs for the key stakeholders.

Technology

- Develop technical capabilities and infrastructures to build, implement, evaluate, monitor and maintain algorithms.
- Align with an IT roadmap.

+



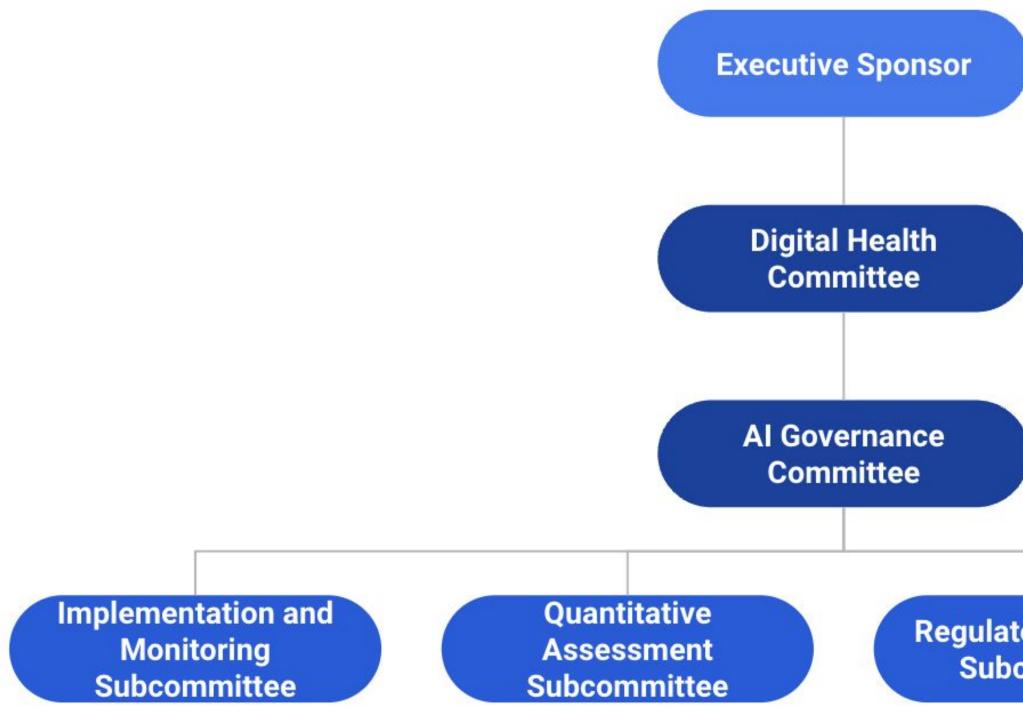
Process (2

Adapt and institutionalize a unified governance process for Al lifecycle management, using a 8 key decision points framework. Document internal Al governance policies.



Establish business plans and operations. Secure resources to put Al governance in place. Establish impact measures.

People Who should oversee AI governance?





Regulatory and Legal Subcommittee

Operation **Subcommittee**



For Example: Membership of ABCDS at Duke

- **Co-Chair (clinical/operational)**: Chief Health Information Officer (Primary care internal medicine)
 - Responsible for overseeing the Ο operation of EHR and clinical and analytic information systems

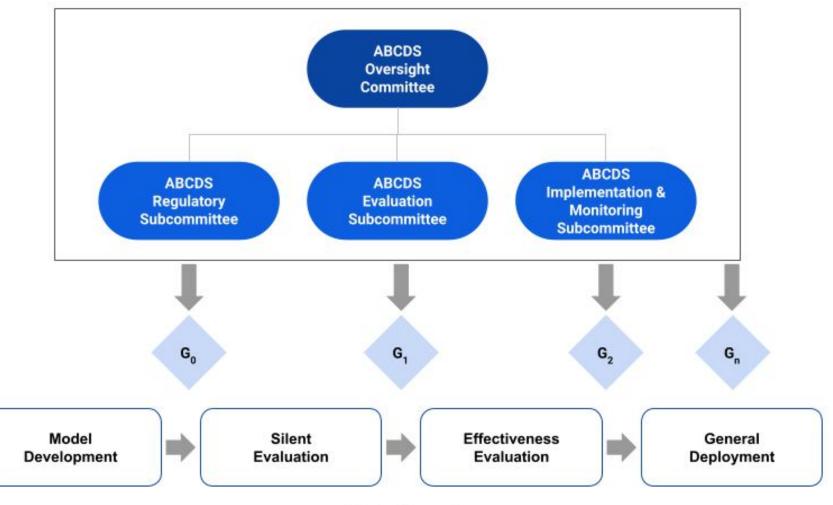
Co-Chair (technical):

Vice dean of data science (Professor of Biostatistics and Bioinformatics)

Responsible for assessing Ο performance and quality of implementation plans

Program Director

Responsible for leading the Ο operations for the governance, evaluation, and monitoring of **ABCDS** software



ABCDS Lifecycle

People

Subcommittee chairs and committee members

- **Regulatory expertise** Ο
- Clinical knowledge Ο
- **Operational experience** Ο
- Quantitative sciences Ο and informatics knowledge Ο
 - Innovation

Expertise & Responsibilities

Domain	Skills and expertise	Responsibilities
Clinical and medical	Clinical knowledge, frontline care, patient needs, Epic, socio technical expertise as end users (i.e., human-computer interaction)	Advise on clinical risks of use and operational value
Technical	Data engineering, data quality, building and evaluating AI, statistics, AI technology, UI/UX, product and solution management	Evaluate the proposed AI implementation by assessing model performance, UI/UX, and solution performance
Social	User research, human-computer interaction, ethnography, critical data studies, science and technology studies	Advise on workflow Identify potential risks of implementation
Informatics	Data quality, data preparation, equity data (i.e., demographic data), software systems, technical systems, technical integration and needs, Epic, security, informatics, strategy	Advise on data quality and availability
Operational	Business strategy, change management and communication, business (e.g., financial, HR, procurement), Epic, operational governance, equity data (i.e., demographic data), patient care operations	Ensure strategic alignment Ensure appropriate engagement and change management plans are in place
Regulatory and legal	Risk management, ethics, technology policy, legal expertise, security, data privacy, compliance	Ensure AI implementation complies with internal policies, procedures, and governance, follows legal requirements and privacy laws and follows ethical principles

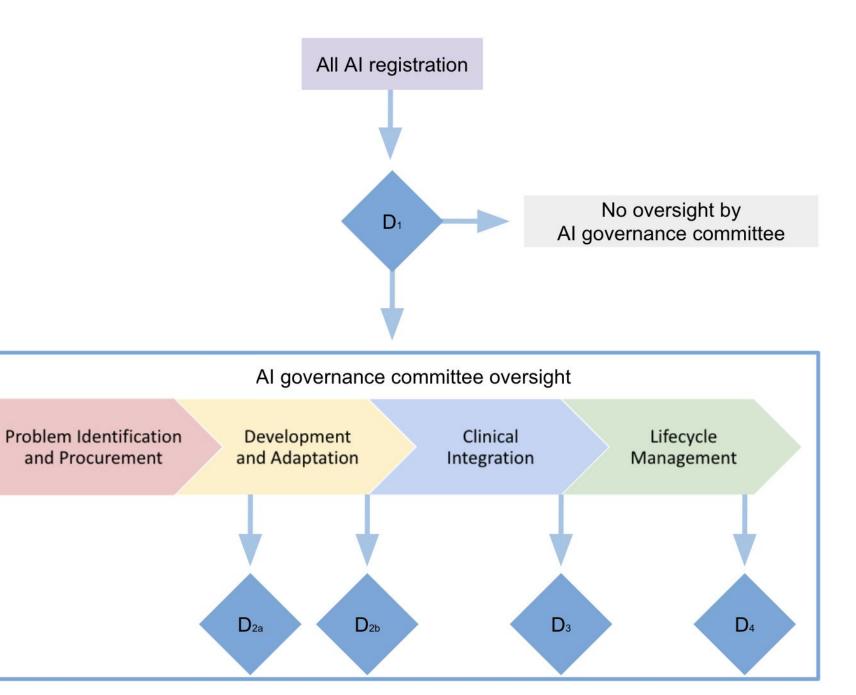


Defining a scope of Al governance

• All AI products should be registered

Full governance	Limited governance
 Al products that interface directly with patients Al products used for clinical documentation (e.g., drafting patient messages and visit notes) Al products used for non-clinical tasks that may limit access to care services (e.g., patient scheduling) Assistive Al products that detect data to aid care provider without analysis or generated conclusions (e.g., rule-based non-ML product) Augmentative Al products that analyze data in a clinically meaningful way Autonomous Al products that interpret data and generate clinically meaningful conclusions without care provider input 	 Al products focused on billing of clinical services Al-driven robotics or automation products used for non-medical purposes (e.g., facility maintenance or logistics management) Al products used for clinical research Al products embedded in regulated hardware devices





Defining a Documentation Requirements

Al lifecycle stage	Information to collect and document	
Problem identification and procurement	 Description of the identified problem Descriptions of scope and intended use of the AI solution Documentation of equity consideration for procurement 	De full to
Development and adaptation	 Model performance targets and measures of successful use Method and results of retrospective evaluation Plans for technical and clinical integration 	De pro
	 Results of prospective silent trial evaluation Model configuration (Threshold selection, Snoozing window) 	De clir
Clinical integration	 User feedback collected via interviews and shadowing and Solution impact Plans for post-integration monitoring and surveillance Plans for ongoing education and training for end users and affected stakeholders 	De the
Lifecycle management	 Ownership of the model Scope of continuous monitoring Cadence of periodic audits Feedback from end users and affected patients Needs for update or decommission Solution impact 	De de sol

Process

Decision to make

Decision 1: Decide which AI products to ally govern and provide recommendations oproject teams for mandatory next steps.

Decision 2a: Approve progressing to a rospective evaluation.

Decision 2b: Approve progressing to linical integration.

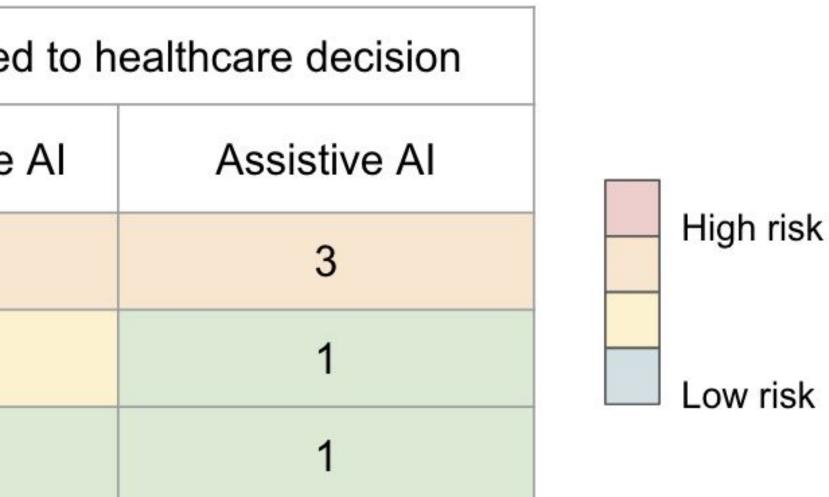
Decision 3: Approve sustaining the use of the Al solution.

Decision 4: Approve sustaining or lecommissioning the use of the Al olution.

Risk Based Al Governance

- Different clinical AI products may be associated with varying levels of risk.
- The AI governance committee can determine the level of risk for each AI product and impose different levels of oversight based on its risk level.

State of healthcare situation or condition	Significance of information provided		
	Autonomous Al	Augmentative	
Critical	4	3	
Serious	3	2	
Non-serious	2	1	



- Reference: IMDRF SaMD Working Group. Software as a medical device: possible framework for risk categorization and corresponding considerations. InInternational Medical Device Regulators Forum 2014.
- https://www.imdrf.org/documents/software-medical-device-possible-framework-risk-categorization-and-corresponding-considerations

Bounds of Enforcement of Al governance

Division of responsibility between the AI governance committee and the department.

 Efficacy (i.e., solution performance) Safety Equity Security and privacy B 	
 Efficacy (i.e., solution performance) Safety Equity Security and privacy B 	
 Alignment with IT roadmap Interoperability with existing enterprise (non-department) software Monitoring and reporting requirements Monitoring threshold settings A 	Clinical Patient I Busines Feasibil Budget Cost eff Interope Software Workfor Cliniciar Account manage

Process

Department or program

- need
- needs
- ss problem that will be addressed
- lity assessment
- fectiveness
- erability with existing department-specific
- e
- rce and workflow burden
- n satisfaction
- tability (i.e., clear product ownership and ement)

Technical Capabilities and Infrastructure Needs

Problem Identification and Procurement

Development and Adaptation

- A tool for clinicians and researchers to register solution requirements and specifications
- A tool to manage and track internal AI governance submissions

•	A system to manage model	٠	Rea
	fact sheets and solution		ofs
	artifacts		0
			0
•	Secure computing		0
	environment for		0
	development and		0
	retrospective validation of		
	algorithms	•	Reg

• A tool to record education and training of end users

Technology

Clinical Integration

Lifecycle Management

al-time validation environment for prospective validation

- solution and lifecycle management
- Data quality monitoring
- Metadata management
- Notification and alerting system
- Outcomes monitoring
- **Operational monitoring**

Registry to store documentation of analyses conducted throughout development, silent validation, and monitoring

Define Resources Needs for Al Governance

- Establish business plans and operations.
 - Develop detailed plans for operationalizing AI governance.
 - Establish a structure for AI governance.
 - Establish communication plans.
- Secure necessary resources to implement AI governance.
 - Personnel
 - Budget
- Establish impact measures and evaluate the success of implementing AI governance.
- Seek feedback from local clinical, regulatory, and patient community members.

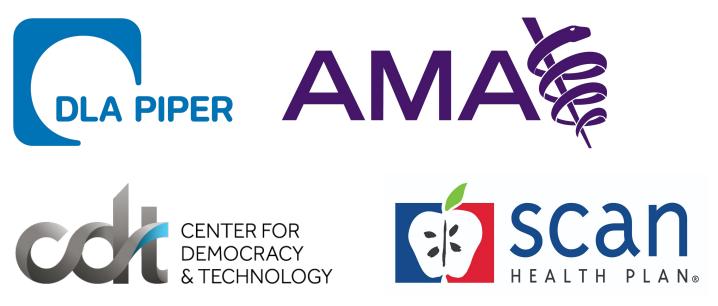
Operations

Engage with our community of practice!





Ecosystem Partners



Federal Agencies





for Health Information Technology *Participating as a federal observer

U.S. Department of Veterans Affairs Veterans Health Administration Office of Discovery, Education and Affiliate Net

Website healthaipartnership.org

Thank you

- Gordon and Betty Moore Foundation
- Health AI Partnership leadership team & Corps Sites
- DIHI Team
- Interview participants
- Workshop participants



- Jee Young Kim
- Mark Sendak
 - Suresh Balu
 - Freya Gulamali
 - Jeffry Hogg
 - Joanne Kim
 - Claire Carroll
 - Shira Zilberstein

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