

STAY
AMAZING

NewYork-
Presbyterian

WITH WORLD-CLASS DOCTORS FROM

COLUMBIA

Weill Cornell
Medicine

Building Safe, Scalable and Useful AI Products for a Health System

Ashley Beecy, MD, FACC | May 12, 2025

Medical Director, Artificial Intelligence Operations at NewYork-Presbyterian
Assistant Professor of Medicine, Division of Cardiology at Weill Cornell Medicine

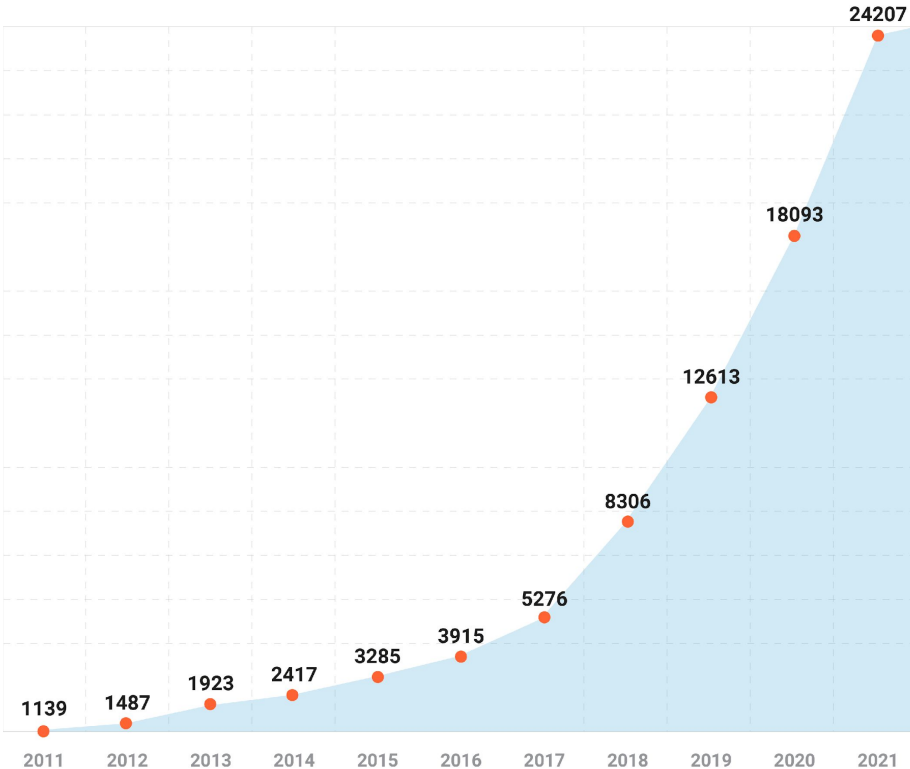






DATE	WEIGHT	BLOOD PRESSURE	PULSE	WEIGHT
8/1	181.0	116/164 97/157 104/157 100/162 106/162 104/167 93/158 101/166 90/160 100/166 100/158	82 72 77 93 86 83 72 99 78	- .8 + .6 + 1.0 + 1.0
8/2	181.6			
8/3	182.6			
8/4	184.4			
8/5	184.2			
8/6	184.8			
8/7	186.7			
8/8	187.4			
	186.3			
				98/60 122/70

NUMBER OF PUBLICATIONS ON THE APPLICATION OF MACHINE LEARNING IN HEALTHCARE IN 2011–2021



<https://pubmed.ncbi.nlm.nih.gov/?term=machine+learning&filter=years.2011-2021&timeline=expanded>

There is exponential growth in the number of machine learning projects representing the multitude of use cases in healthcare.

What Makes Healthcare Different?

Identifying the Problem



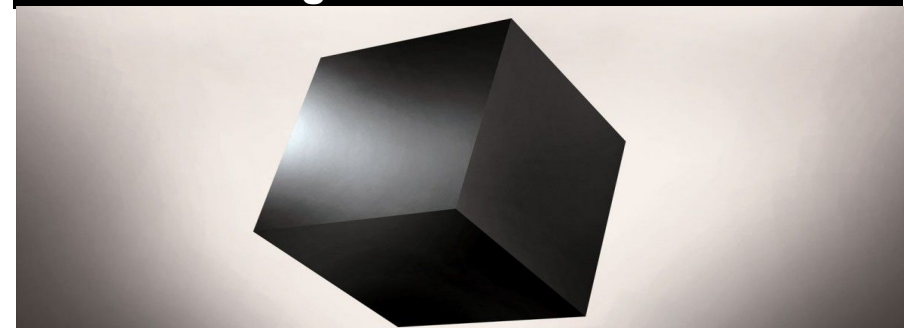
AI Deployment



Solution Performance



Regulation and Trust



Identifying the Problem | What is relevant?

- Understand **org-wide priorities** and challenges
- Assess **current workflow** and solution
- Spot issues and propose **practical, fast solutions**
- Plan **model integration** and affected roles
- Compare AI with **simpler or cheaper alternatives**
- Confirm **data and labels are available**
- Outline key **components for success**



Heart Failure Has Widespread Societal Impacts

>8,000,000

of adults with heart failure in the U.S. by 2030

1:5

Lifetime risk of developing HF for both men & women >40

\$69,700,000,000

\$ spent by U.S. health care annually on heart failure

- Goal: Transform cardiovascular health and heart disease prediction and prevention
- Approach: Apply AI and machine learning to multi-modal data to screen for heart failure, predict progression, and inform care decisions

NewYork-Presbyterian, Cornell Tech and the Cornell Ann S. Bowers College of Computing and Information Science Collaborate to Transform How Health Care is Delivered

Organizations will advance cardiovascular medicine with the use of advanced analytics and artificial intelligence, moving towards prediction and prevention of heart disease.

Jul 14, 2022

New York, NY



Identifying the Problem | Cardio AI Collaboration

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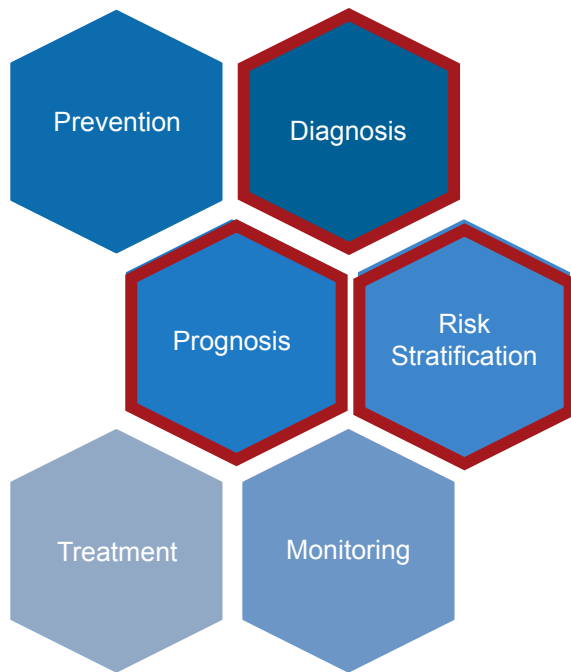


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How do you get started?

Areas of Focus



Topics of Interest

- ✓ Heart Failure Reduced Ejection Fraction
 - LVAD
 - Transplant
- ✓ Cardio-Oncology
- ✓ Heart Failure Preserved Ejection Fraction
 - Cardiac Amyloidosis
- ✓ Hypertrophic Cardiomyopathy
 - Valvular Disease
 - Myocarditis
 - Cardiac Sarcoidosis

Identifying the Problem | Cardio AI Collaboration



Prognosticate
using multimodal
data sources



Identify disease
processes with
low cost readily
available data



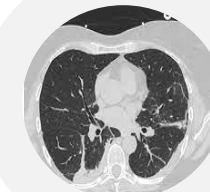
Understand
severity of illness
and management



Screen for
transition to
advanced heart
failure

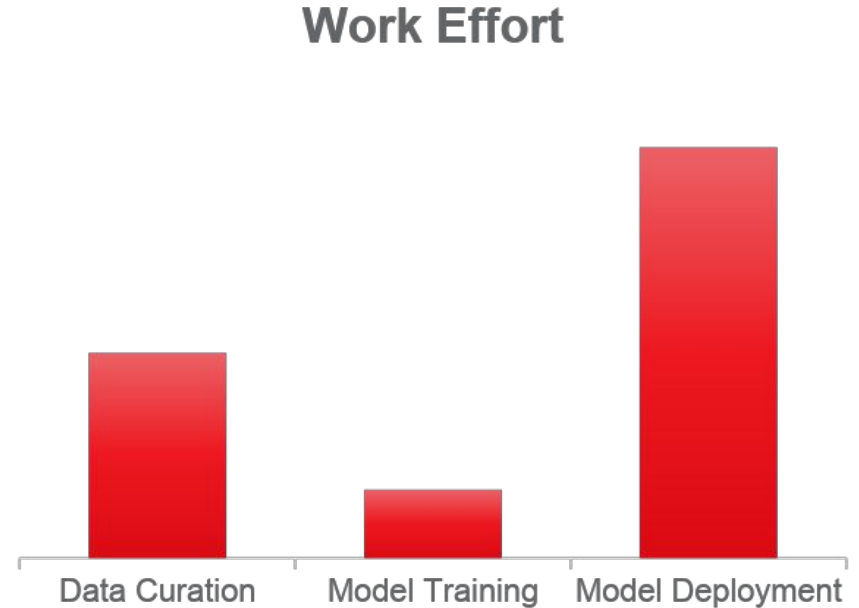
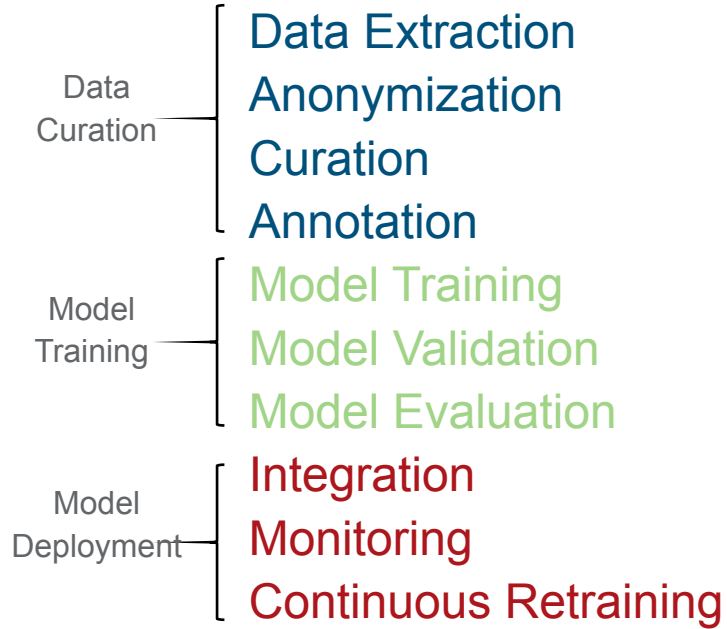


Model disparities
in healthcare

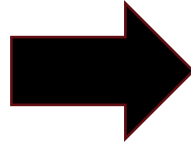


Screen for cardiac
pathology on
existing scans

AI Development | Life Cycle

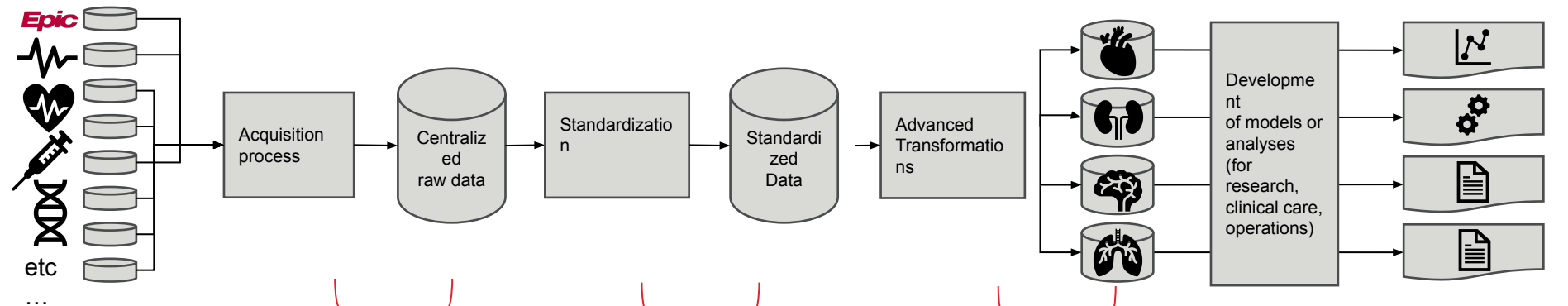


AI Development | Cardiovascular Data Infrastructure



AI Development | Cardiovascular Data Infrastructure

Raw data spread across
systems/vendors/
campuses



- **Hardware upgrade**
- **Imaging data pipeline**
- **System integrations**

- **National registries**
- **EHR Registries**
- **Echo data tables**
- **IDCO**

- **EP research repository**
- **ACHD research repository**
- **HF research repository**

- **Data archiving**

- **Standardized**

Electrocardiogram (ECGs)

- ECG machine upgrades to transmit all ECGs centrally
- Prospective “printing” to .xml files
- Conversion of >10 million ECGs to .xml files

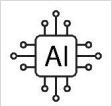
TABLE NAME	DESCRIPTION
stg_muse_site0001_diagnosis	staging table for ecg diagnosis text
stg_muse_site0013_diagnosis	staging table for ecg diagnosis text
stg_muse_site0001_patientdemographics	staging table for ecg patient demographics
stg_muse_site0013_patientdemographics	staging table for ecg patient demographics
stg_muse_site0001_ecgmeasurements	staging table for ecg measurements
stg_muse_site0013_ecgmeasurements	staging table for ecg measurements
stg_muse_site0001_testdemographics	staging table for ecg study information
stg_muse_site0013_testdemographics	staging table for ecg study information
ecg_key_link	reference table to crosswalk source ecg ids to model keys
ecg_study	table which contains ecg study information
ecg_diagnosis_text	table which contains ecg diagnosis text information
ecg_measurements	table which contains ecg measurement information



AI Development | Cardiovascular Data Infrastructure

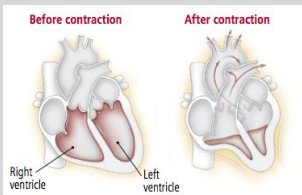
Epic_MedicationID	GenericName	Epic_GenericID	PHARM_CLASS	PHARM_SUBCLASS	HF_Class
71705	Ezetimibe-Simvastatin	3999400230	Antihyperlipidemic	Antihyperlipidemics - Combinations	Antihyperlipidemics - Combinations
142237	Icosapent Ethyl	3950003510	Antihyperlipidemic	Antihyperlipidemics - Misc.	Antihyperlipidemics - Misc.
51610	NULL	3699100220	Antihypertensive	Antihypertensive Combinations	Antihypertensives - Misc.
111566	amLODIPine Besylate-Valsartan	3699300210	Antihypertensive	Antihypertensive Combinations	Calcium Channel Blockers
10637	Acetazolamide Cap ER 12H	3710001000	Diuretics	Carbonic Anhydrase Inhibitors	Carbonic Anhydrase Inhibitors
5231	Digoxin Tab 125 MCG (0.125 mg)	3120001000	Cardiotonics	Cardiac Glycosides	Cardiac Glycosides
47559	Cardioplegic Soln	4020001000	Cardiovascular Age	Cardioplegic Solutions	Cardioplegic Solutions
114764	Aliskiren-Hydrochlorothiazide	3699600215	Antihypertensive	Antihypertensive Combinations	Direct Renin Inhibitors
50775	Buchu-Cornsilk-Ch Grass-Hawthorn	3799200410	Diuretics	Diuretic Combinations	Diuretics - Miscellaneous
31494	Fenofibrate Micronized Capsules	3920002510	Antihyperlipidemic	Fibric Acid Derivatives	Fibric Acid Derivatives
24739	Carvedilol Tab 3.125 MG	3330000700	Beta blockers	Alpha-Beta Blockers	HF Beta Blocker
44726	Spironolactone-HCTZ	3799000220	Diuretics	Diuretic Combinations	HF Potassium Sparing Diuretics
7691	Pravastatin Sodium Tab 20	3940006510	Antihyperlipidemic	HMG CoA Reductase Inhibitors	HMG CoA Reductase Inhibitors
96483	Isosorb Dinitrate-hydrALAZ	4099500240	Cardiovascular Age	Cardiovascular Agents Misc. - Combination	Hydralazine
115479	Tadalafil Tab 2.5 MG	4030408000	Cardiovascular Age	Impotence Agents	Impotence Agents
145568	Milrinone Lactate in Dextrose	3135005011	Cardiotonics	Inotropes	Inotropes
39265	Ezetimibe Tab 10 MG	3930003000	Antihyperlipidemic	Intestinal Cholesterol Absorption Inhibitors	Intestinal Cholesterol Absorption Inhibitors
162255	Furosemide in Sodium Chloride	3720003010	Diuretics	Loop Diuretics	Loop Diuretics
129051	Nitroglycerin Cap ER 6.5 M	3210003000	Antianginal agents	Nitrates	Nitrates

Echo - VO2



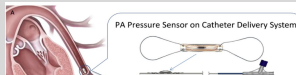
Echo □ VO₂

CT - EF



CT □ LVEF

Remote Management



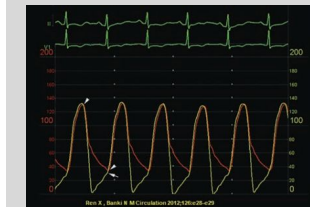
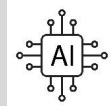
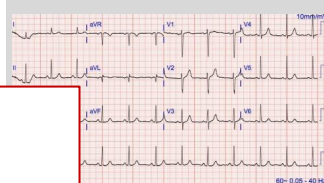
Device □ Treatment

Remission - HF



Echo □ LV Recovery

ECG - Dynamics



ECG □ Hemodynamics

Opportunistic screening is the practice of detecting diseases or health risks during routine clinical care, even when the patient isn't being evaluated specifically for that condition.

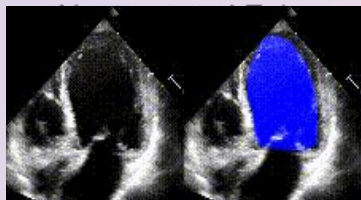
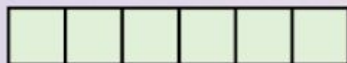
- 5–25% of heart failure patients progress to advanced stages (~200,000/year).
- 1-year survival without advanced therapies is 25–50%; only ~6,000 receive advanced treatments annually.
- Echocardiography is commonly available but limited in estimating mortality.
- Cardiopulmonary exercise testing (CPET) is a strong mortality predictor but requires specialized equipment and expertise, limiting accessibility.



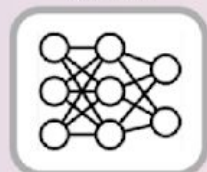
Workflow

Data Collection and Preprocessing

Structured Features



Multi-Modality Model



Echo- VO2

Predicting Peak VO2 Based on Deep Learning

Predicted Peak VO2



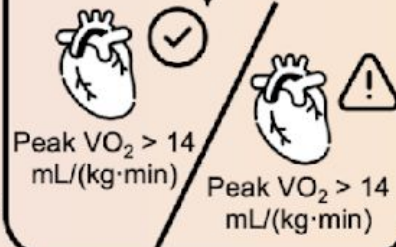
True Peak VO2

Application to HF Cohorts



Screening with Predicted Values as Scores

Predicted Value



Results

Development Cohort



- NewYork-Presbyterian/Columbia University Irving Medical Center
- 1,000 CPET Studies

- (Regression) R2 Score: 0.560
- (Binary Classification) AUROC: 0.839

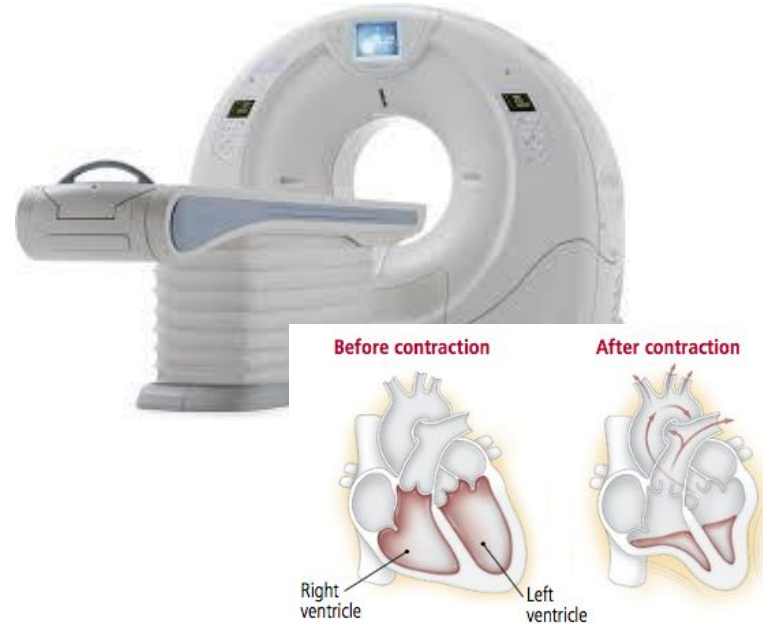
External Validation Cohort



- NewYork-Presbyterian/Weill Cornell Medical Center
- NewYork-Presbyterian/Brooklyn Methodist Hospital
- NewYork-Presbyterian/Queens Hospital
- 127 CPET Studies

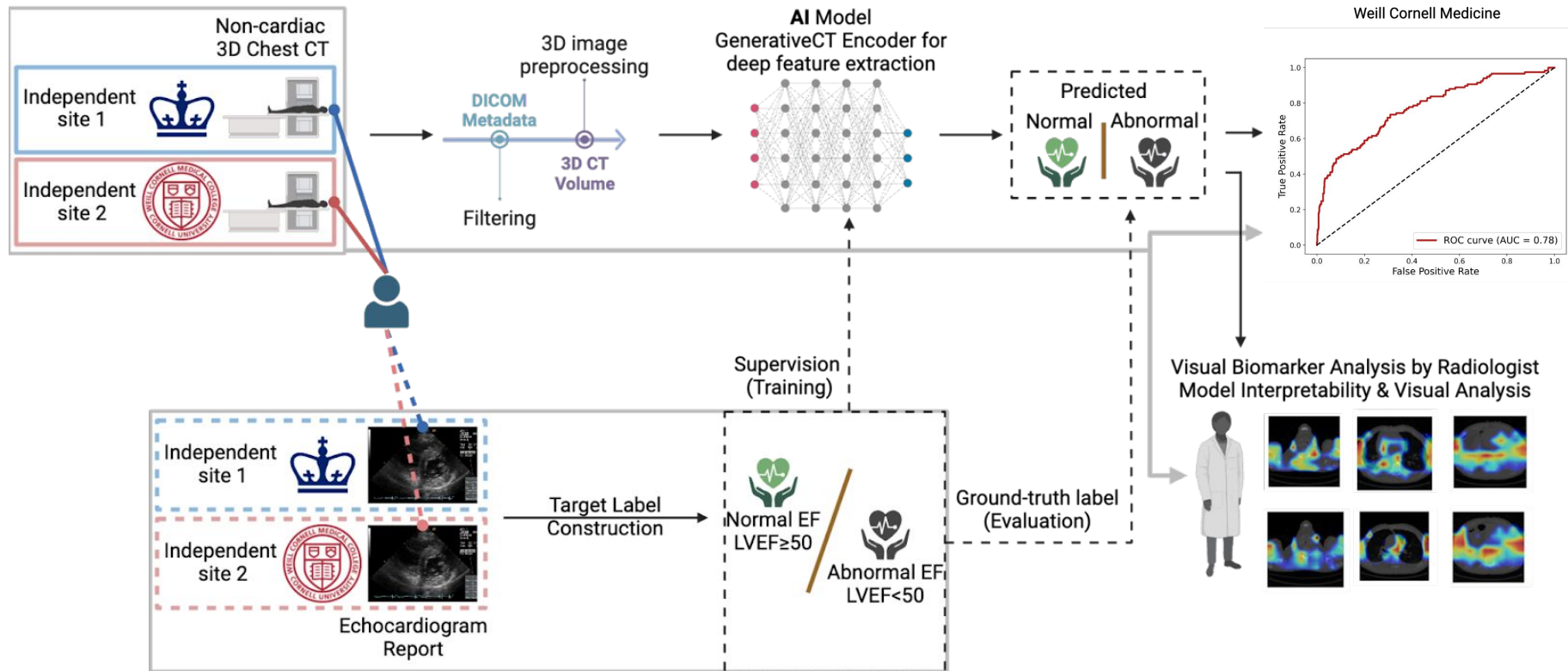
- (Regression) R2 Score: 0.434
- (Binary Classification) AUROC: 0.809

- Over 80 million computed tomography scans(CTs) are performed in the US yearly.
- Many CTs ordered for non-cardiac indications.
- Opportunity to identify patients early that would benefit from optimal heart failure care.

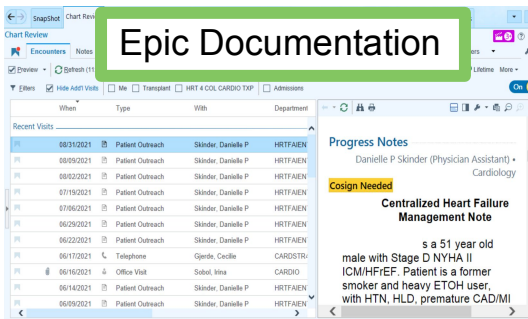
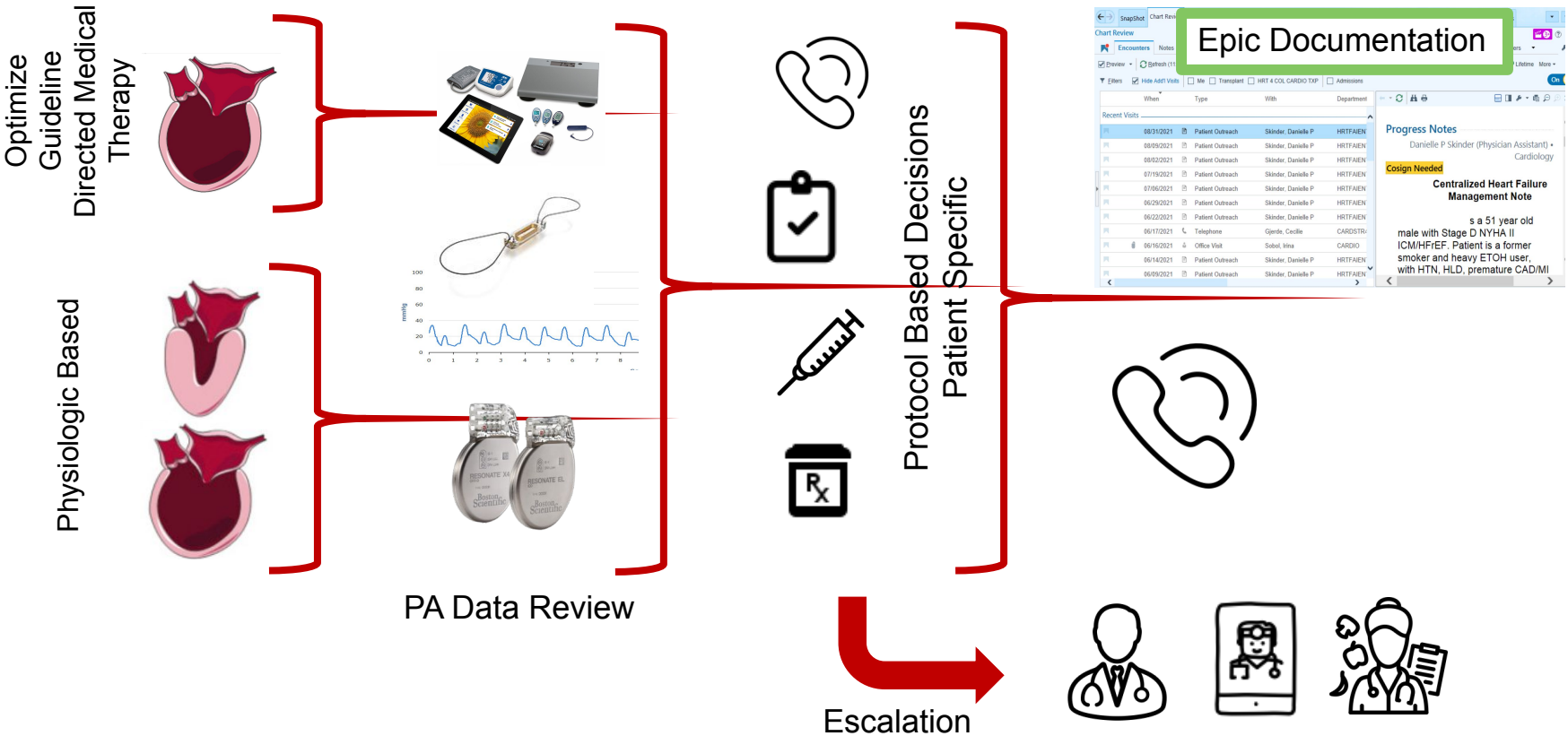




Weill Cornell Medicine

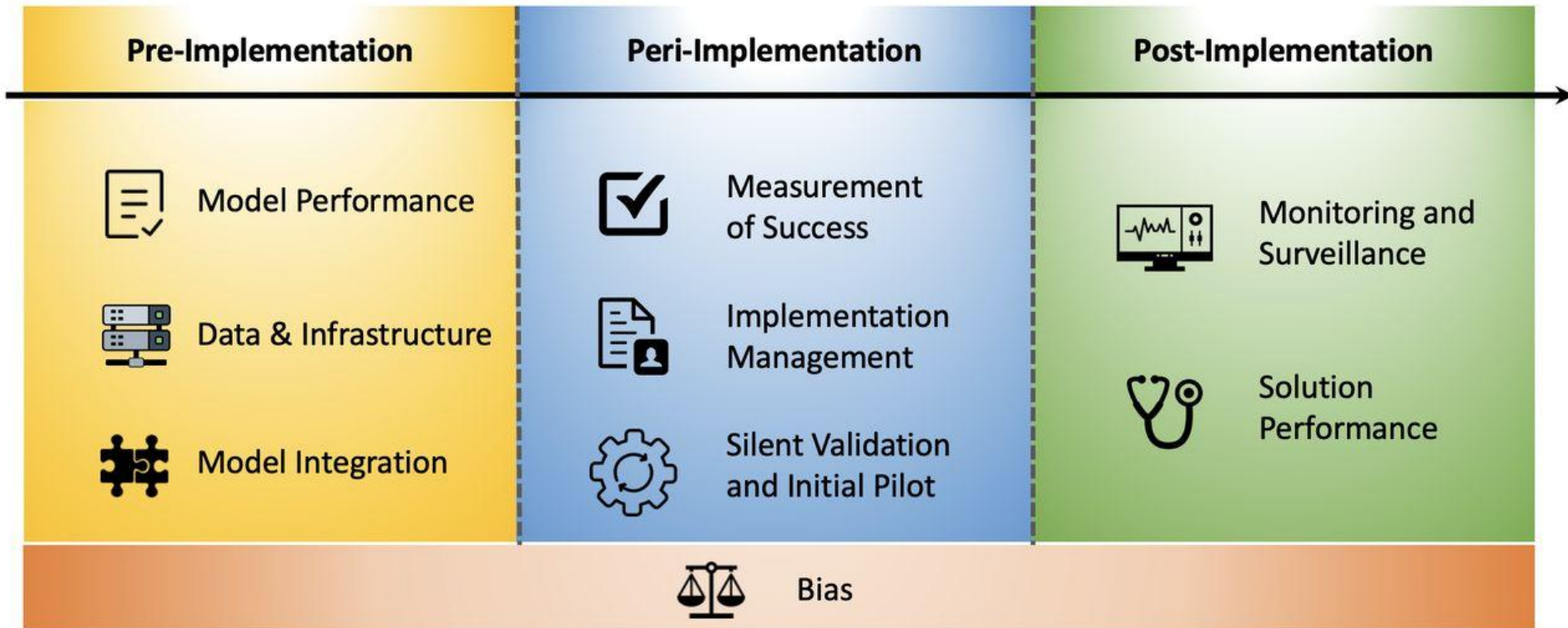


AI Development | Centralized Remote Management Program



AI is poised to transform medicine if we can empower our providers by *effectively delivering* this assistive technology into the healthcare system.

AI Deployment | Process Flow



AI Deployment | Sample Model Integration Points

BestPractice Advisory - Smith,

Critical (1)

The predictive model for risk of opioid abuse or overdose has identified nonpharmacologic and nonopioid therapies before prescribing opioid.

Remove the following orders?

Remove Keep

hydrocodone-acetaminophen (NORCO) 5-325 MG per tablet
1 tablet, Oral, EVERY 4 HOURS PRN starting 4/6/2018, Disp-30 each, R-0, Norm

Apply the following?

Order Do Not Order

acetaminophen (TYLENOL) tablets 1,000 mg

Order Do Not Order

NALOXONE HCL 4 MG/0.1ML NA LIQD

Curry, Che

Treatment Team: None

Male, 20 yo, 03/09/1996

Department Appointments Report: Check In - Primary Care

Refresh Settings AppJ Desk Walk In Sign In Check In Check Out Room Patient Assign Tablet Appt Inf

Full Appointment List Appointment Totals

Date 11/30/2017 Department: EMC FAMILY MEDICINE[10501101]

Ap	Appt Time	Wait Time (Afte	Status	NS Chance	Conf?	Pt Info
	8:00 AM		Sch	97 %		Douglas, Crystal
	8:15 AM		Sch	23 %	✓	Newton, Seth
	8:30 AM		Sch	12 %	✓	Hart, Barry
	8:30 AM		Sch	74 %		Alvarez, Sonya
	8:45 AM		Sch	27 %		Carlson, Kenny
	9:00 AM		Sch	23 %	✓	Woods, Tanya
	9:30 AM		Sch	6 %	✓	Gomez, Judy
	9:30 AM		Sch	10 %	✓	Sandoval, Allison
	9:45 AM		Sch	15 %	✓	Adams, Dale

Deterioration Index

Johnson, Lori M - Score calculated just now

View model formula and coefficients

Mark as Reviewed

31

Medium

High: 50 - 100
Medium: 30 - 50
Low: 0 - 30

Time

Factors Contributing to Score

Factor	Contribution	Most Recent Value
Age	34%	63 years old
Hematocrit	<1%	40.0 %
Potassium	5%	4.2 mEq/L *
Pulse	<1%	67
Pulse oximetry	5%	92 %
Respiratory rate	42%	26
Sodium	4%	142 mEq/L *
Systolic	1%	118
Temperature	<1%	36.9 °C (98.5 °F)
WBC count	8%	abnormal (11 X 10E9/L)

Search All Admitted P...

DETERIORATION INDEX Score Column

40

31

27

27

27

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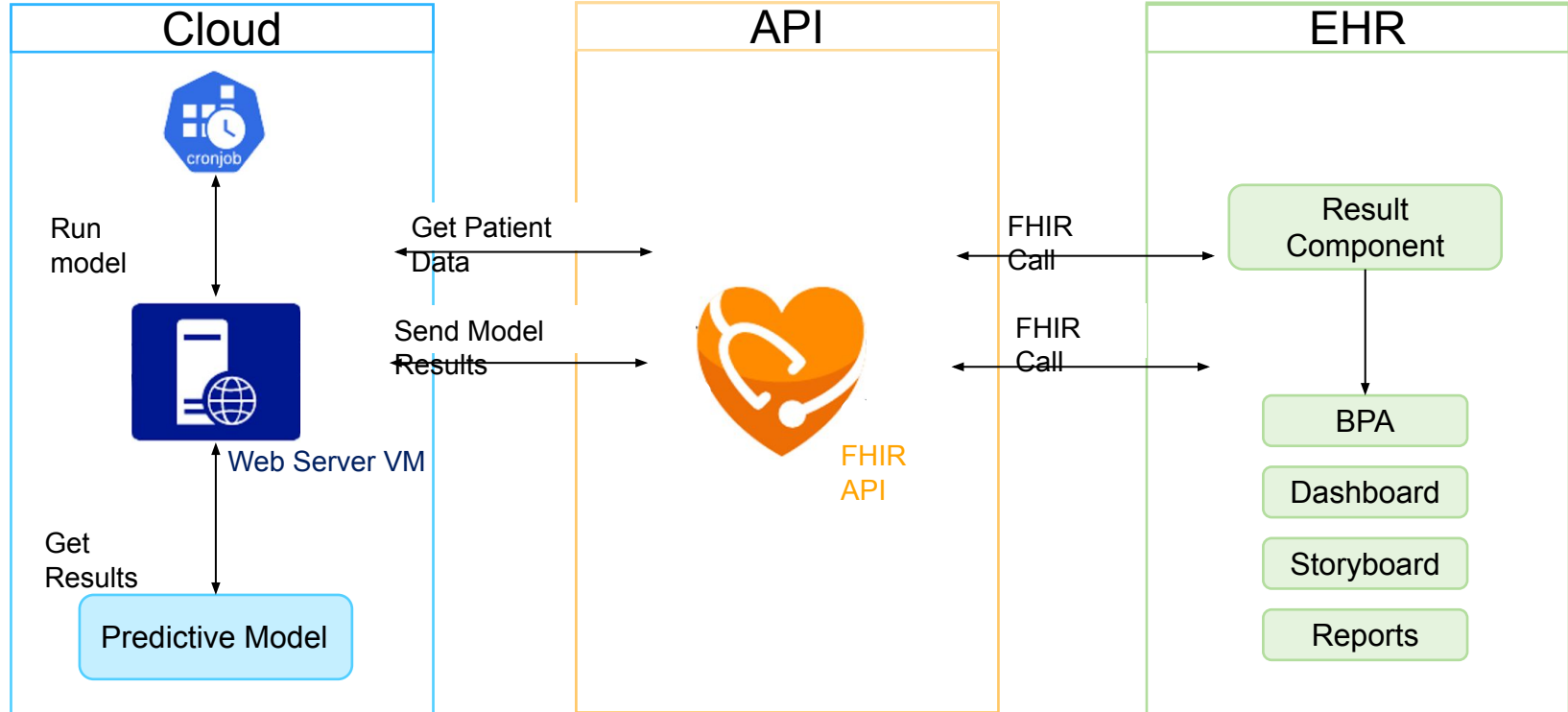
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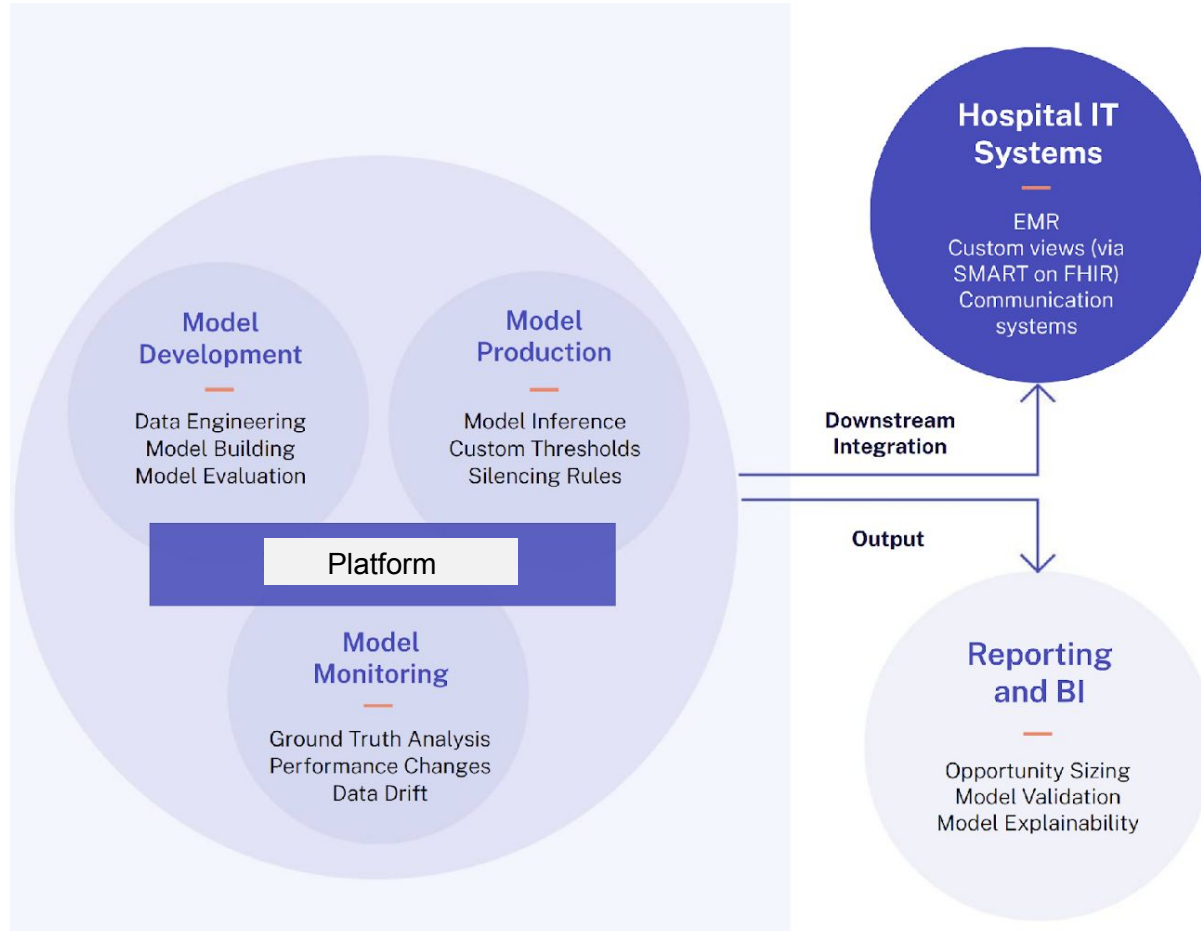
27

This is not real patient data.

AI Deployment | Sample Model Architecture



Solution Performance | Monitoring and Surveillance



Model Monitoring

- Inputs/Outputs
- Data Drift
- Performance

Technical Monitoring

- Run times
- Security
- Version control

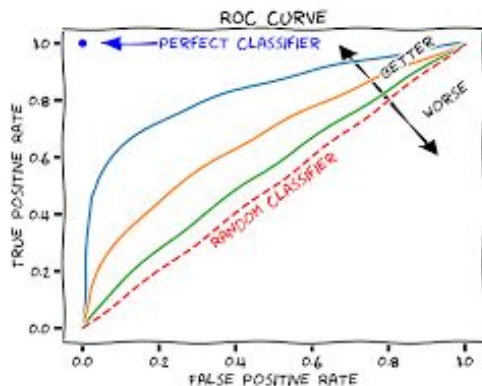
Solution Monitoring

- Outcomes
- Usability
- Feedback

Regulatory and Compliance

- Policy adherence
- Health equity
- Federal regulations

The solution performance is more than an AUC



An AI solution requires contextual assessment



Determine the testable metrics at the initiation of integration

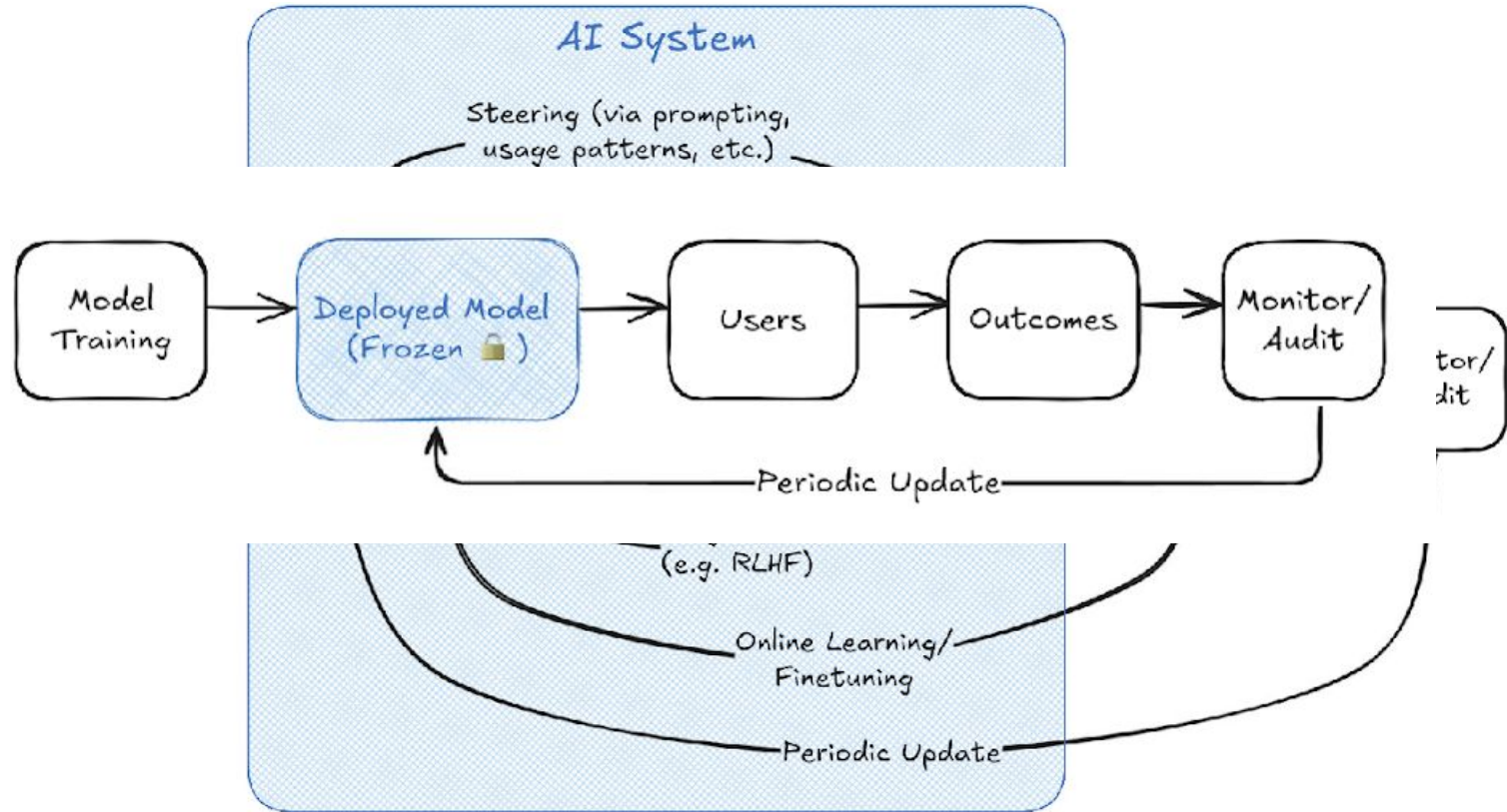


Compare the metrics to standard of clinical care before integration



Consider ability to measure the metrics and the resources involved

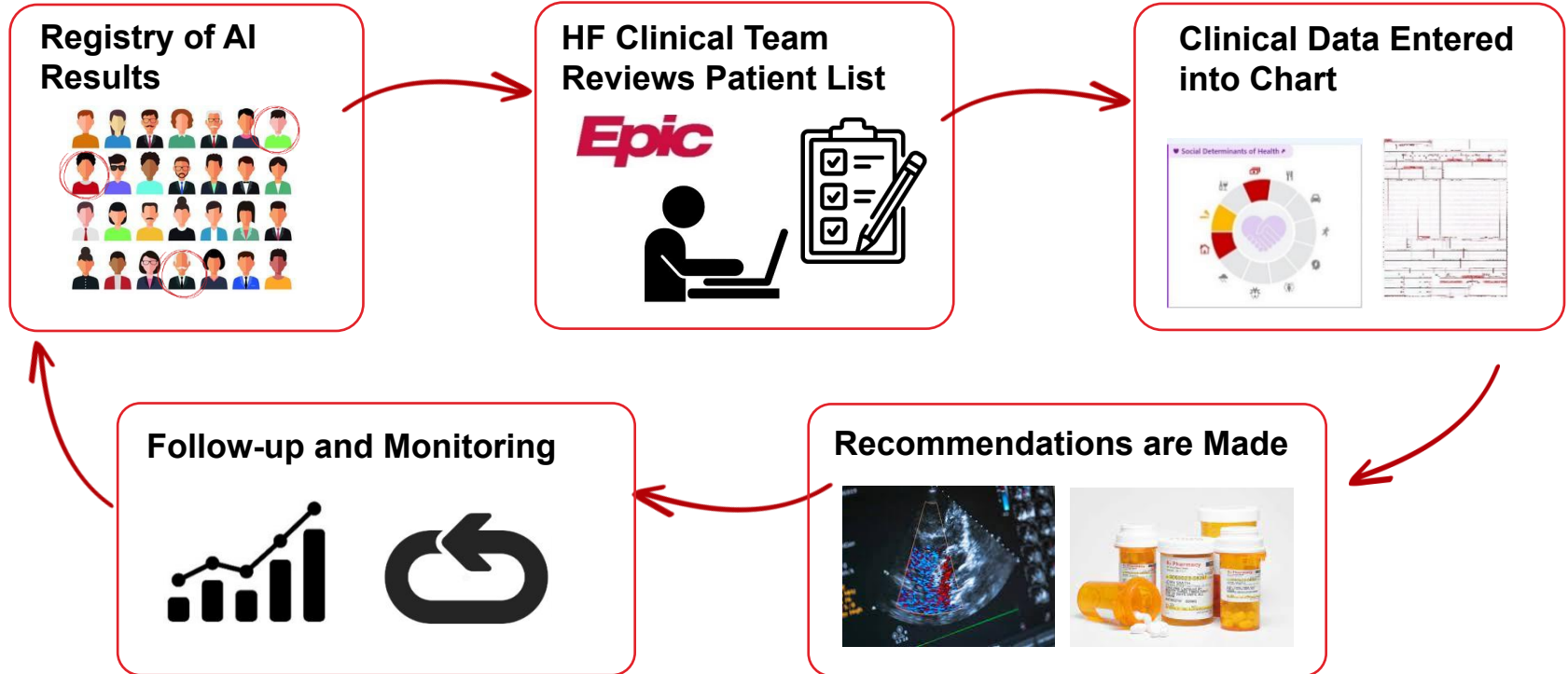
Solution Performance | Adaptive Systems



Rosenthal, Jacob T., Ashley Beecy, and Mert R. Sabuncu. "Rethinking clinical trials for medical AI with dynamic deployments of adaptive systems." *npj Digital Medicine* 8.1 (2025): 1-6.

Transparency and Trust | A Heart Failure Learning Health System

An iterative process where the AI model's outputs are continuously collected.



Solution Performance | Governance



Solution Performance | Governance

Risk to patient privacy

Through secondary use of patient data in AI model training and inference

Risk to the quality of patient care

Through substitution of medical judgment by AI technology

Regulatory risk

If our use of AI does not meet regulatory requirements, e.g., for nondiscrimination

OPEN ACCESS Freely available online

PLoS ONE

A Systematic Review of Re-identification Attacks on Health Data

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Abstract

Background: Privacy legislation in most jurisdictions allows the disclosure of health data for secondary purposes without patient consent if it is de-identified. Some recent articles in the medical, legal, and computer science literature have argued that de-identification methods do not provide sufficient protection because they are easy to reverse. Should this be the case, it would have significant and important implications on how health information is disclosed, including: (a) potentially limiting its availability for secondary purposes such as research, and (b) resulting in more identifiable health information being disclosed. Our objectives in this systematic review were to: (a) characterize known re-identification attacks on health data and contrast that to re-identification attacks on other kinds of data, (b) compute the overall proportion of records that have been correctly re-identified in these attacks, and (c) assess whether these demonstrate weaknesses in current de-identification methods.

Methods and Findings: Searches were conducted in IEEE Xplore, ACM Digital Library, and PubMed. After screening, fourteen eligible articles representing distinct attacks were identified. On average, approximately a quarter of the records were re-identified across all studies (0.26 with 95% CI 0.046–0.478) and 0.34 for attacks on health data (95% CI 0–0.746). There was considerable uncertainty around the proportions as evidenced by the wide confidence intervals, and the mean proportion of records re-identified was sensitive to unpublished studies. Two of fourteen attacks were performed with data that was de-identified using existing standards. Only one of these attacks was on health data, which resulted in a success rate of 0.0003.

Conclusions: The current evidence shows a high re-identification rate but is dominated by small-scale studies on data that was not de-identified according to existing standards. This evidence is insufficient to draw conclusions about the efficacy of de-identification methods.

Citation: El Emam K, Jonker E, Arbućkle L, Malin B (2017) A Systematic Review of Re-identification Attacks on Health Data. PLoS ONE 12(12): e0182711. doi:10.1371/journal.pone.0182711

Editor: Roberto W. Schrier, Johns Hopkins Bloomberg School of Public Health, United States of America

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Funding: This study was funded by grant nos. 1011046000000 and 1011046000000 from the National Institutes of Health and a grant from the Canada Research Chairs program. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing Interests: The authors have read and approved the journal policy and have the following conflicts: all co-authors perform consulting to federal and provincial governments and commercial entities in the US and Canada on de-identification, EHR, and Big data on federal and provincial government, advisory committees related to health information privacy. This does not alter the authors' adherence to all the PLoS ONE policies on sharing data and materials.

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Original Investigation

June 21, 2021

External Validation of a Widely Implemented Proprietary Sepsis Prediction Model in Hospitalized Patients

Andrew Wong, MD¹; Erkin Otles, MEng^{2,3}; John P. Donnelly, PhD⁴; Andrew Krumm, PhD⁴; Jeffrey McCullough, PhD⁵; Olivia DeTroyer-Cooley, BSE⁶; Justin Pestruie, MEd⁶; Marie Phillips, BA⁷; Judy Konye, MSN, RN⁸; Carleen Penzoza, MHSA, RN⁸; Muhammad Ghous, MBBS⁴; Karandeep Singh, MD, MMS^{1,4}

Author Affiliations | Article Information

JAMA Intern Med. 2021;181(8):1065-1070. doi:10.1001/jamainternmed.2021.2626

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RESEARCH ARTICLE

f X in

Dissecting racial bias in an algorithm used to manage the health of populations

ZIAD OBERMEYER¹, BRIAN POWERS, CHRISTINE VOGEL, AND SENSU MULLANAATHAN² Authors Info & Affiliations

SCIENCE • 23 OCT 2019 • Vol 366, Issue 5464 • pp. 447-453 • DOI:10.1126/science.aaa2262

121,740 99 1,266

Share

Racial bias in health algorithms

The U.S. health care system uses commercial algorithms to guide health decisions. Obermeyer *et al.* find evidence of racial bias in one widely used algorithm, such that Black patients assigned the same level of risk by the algorithm are sicker than White patients (see the Perspective by Benjamin). The authors estimated that this racial bias reduces the number of Black patients identified for extra care by more than half. Bias occurs because the algorithm uses health costs as a proxy for health needs. Less money is spent on Black patients who have the same level of need, and

Slide courtesy of Beth Percha

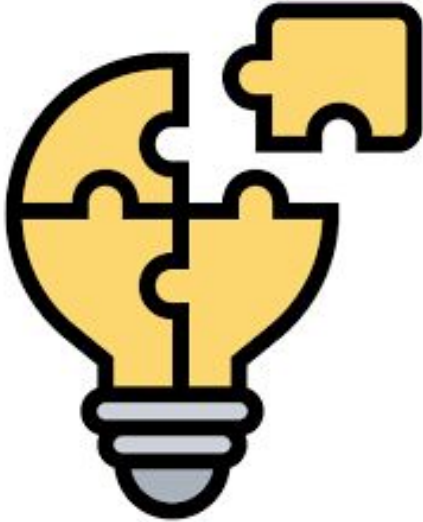
National Organizations



Advocacy



Summary



- Spend time up front understanding the problem, the proposed integration and the resources needed
- Verify the presumed value propositions via testing in real-world integration
- Understand the performance with integration includes more than the technical metrics
- Build consensus and trust with stakeholder involvement, transparency and communication

Questions