<u>Revolutionizing Point of Care Medicine</u> Harnessing AI, Cognitive Decision Support, and Living Guidance for Physicians



Christopher Tignanelli, MD MS FACS FAMIA

Associate Professor of Surgery

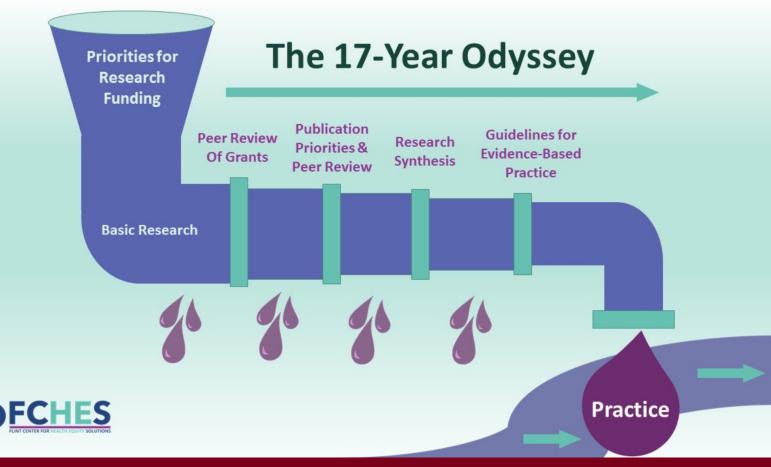
Associate Dean of Data Science

Affiliate Faculty, Institute for Health Informatics

Scientific Director, Program for Clinical Artificial Intelligence Director, UMN Center for Quality Outcomes, Discovery and Evaluation



We still suffer from an evidence to practice translation gap



17 years for14% of originalresearch tobenefit patients

Balas, 1998; Balas and Boren, 2000; Green et al., 2009



And even when we do get evidence into guidelines time constraints limit our ability to deliver best practice

<u>J Gen Intern Med.</u> 2023 Jan; 38(1): 147–155. Published online 2022 Jul 1. doi: <u>10.1007/s11606-022-07707-x</u> PMCID: PMC9848034 PMID: <u>35776372</u>

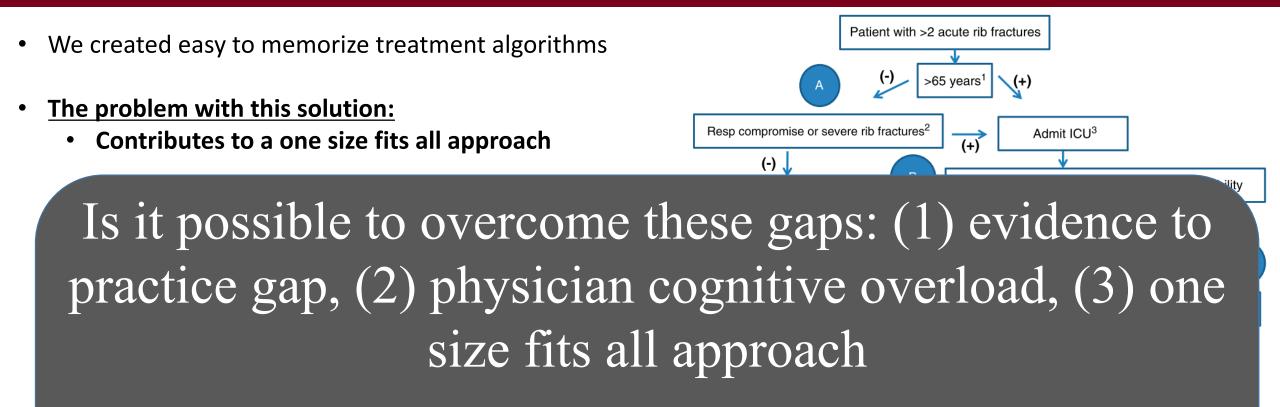
Revisiting the Time Needed to Provide Adult Primary Care

Justin Porter, MD,^{II} Cynthia Boyd, MD, MPH,² M. Reza Skandari, PhD,³ and <u>Neda Laiteerapong</u>, MD, MS⁴

"Our study found that a primary care physician (PCP) would need an infeasible 26.7 hours per day to provide preventive, chronic disease, and acute care for an average US adult patient."



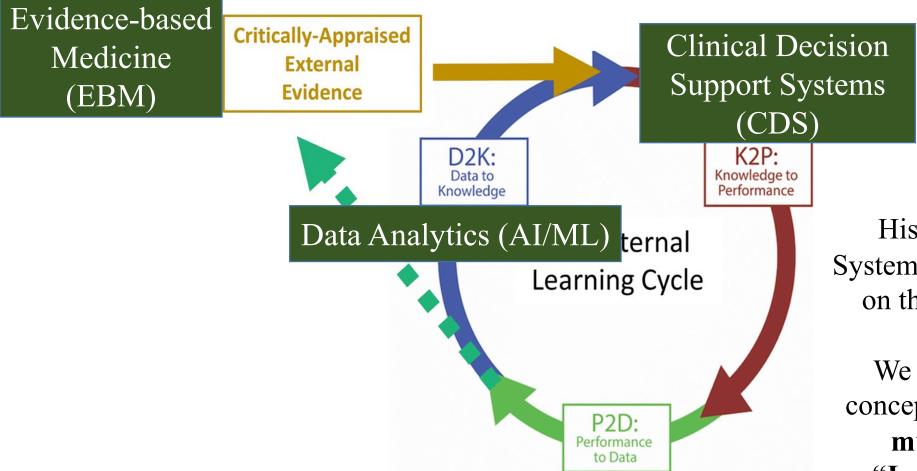
One thing done to help remedy this problem



and transform medical delivery to provide more efficient evidence-based and personalized care?

Br

The Learning Health System integrates three disciplines: EBM + AI/ML + CDS



Historically, Learning Health Systems have primarily concentrated on the **healthcare system level**.

We need to aim to elevate this concept to a national scope linking **multiple systems within a "Learning Health Network"**

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What is Clinical Decision Support?



M Health Fairview COVID-19 Anticoagulation Pharmacy Guide for

NON-Pregnant ADULTS (> 18 years old) with COVID-19

(Modified from the UNC Chapel Hill Protocol) Revision Date: 7/14/20

UMMC - Non-Malignant Hematology Section, Division of Hematology, Oncology, and Transplantation

Highly suspected or confirmed ADULT, NON-Pregnant*** COVID-19+ patient

***Please consult OB provider for pregnant/breastfeeding women who are COVID-19 positive (Pregnancy OB Admission Recommendations during COVID-19)

Labs on admission: D-dimer, reticulocyte count, PT/INR, aPTT, fibrinogen, Antithrombin, ferritin, LDH, CMP and CBC with diff Daily Labs: D-dimer, reticulocyte count, PT/INR, aPTT, fibrinogen, CBC with diff

VTE prophylaxis for ALL hospitalized highly-suspected or confirmed COVID-19+ patients

D-dimer < 10 x ULN[#] and NO other Risk Factors^{\$}

eGFR* >/= 30 mL/min

- BMI > 40 kg/m²: Enoxaparin 40 mg SQ BID^{**}
- BMI 18-40 kg/m²: Enoxaparin 40 mg SQ Q24 Hrs
- BMI < 18 kg/m²: Enoxaparin 30 mg SQ Q24 Hrs
- Enoxaparin anti-Xa goal = 0.3-0.5. Testing only recommended if concern for under or over-treatment.

<u>eGFR* < 30 mL/min</u> Heparin 5,000 units SQ q8 Hrs

If pharmacologic prophylaxis contraindicated (active bleeding, PLT < 30,000): Apply SCDs D-dimer ≥ 10 x ULN[#] <u>AND/OR</u> in the ICU, active cancer OR history of VTE

eGFR* >/= 30 mL/min

Enoxaparin 0.5 mg/kg BID^{**} (Max dose = 90 mg) Check Enoxaparin anti-Xa on any dose > 80 mg. Target Enoxaparin anti-Xa (4 hrs after 4th dose) = 0.4-0.7

eGFR* < 30 mL/min

- HealthEast: Heparin LOW Intensity Protocol HE Heparin-Xa goal = 0.25-0.6
- Fairview: COVID Heparin Protocol FV Heparin-Xa goal = 0.25-0.5

If pharmacologic prophylaxis contraindicated (active bleeding, PLT <30,000): Apply SCDs

Therapeutic anticoagulation

On therapeutic anticoagulation prior to admission

 Continue PTA anticoagulation if no contraindications Highly-suspected or confirmed VTE

eGFR*>/= 30 mL/min

Enoxaparin 1 mg/kg SQ BID^{**} (Max dose= 190 mg) Check Enoxaparin anti-Xa on any dose > 140 mg. Target Enoxaparin-Xa (4 hrs after 4th dose) = 0.6-1.

<u>eGFR*<30 mL/min</u> IV UFH HIGH-intensity protocol Heparin-Xa goal = 0.3-0.7

Clinical Decision Support to deploy COVID-19 clinical practice guidelines

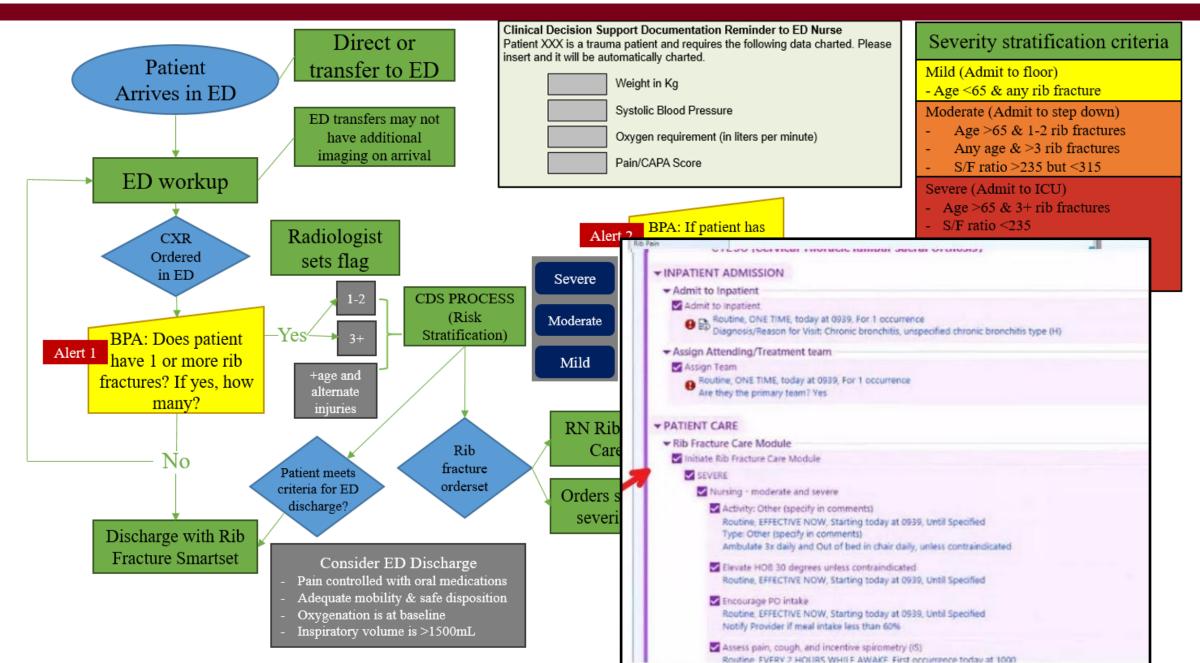
Supplemental Figure 2: Screenshots of COVID-19 anticoagulation clinical decision support system's passive and interruptive elements

Passive COVID-19 Anticoagulation Orderset	Interruptive BPA within Admission Orderset Navigator
HEM Covid-19 Anticoagulation ADULT Image User Versions MAY-2020 (3040001975) Content Owner: SL Cancer Care – Benign Hematology Intended for use ONLY with Covid-19 Positive patient greater than or equal to 18 years of age and non-pregnant females. Image User Version: GENERAL Provider Guidance ALL patients admitted to hospital should get pharmacologic thromboprophylaxis unless contraindicated. Antiplatelet therapy alone is not felt to be adequate anti-thrombotic prophylaxis in COVID-19 patients. All ICU COVID-19 Positive patients are recommended for category B or C Intensity Anticoagulation to prevent thrombosis unless contraindication. IF patient already on therapeutic intensity anticoagulation, select that option below. Hospitalized patients should be categorized into 3 risk categories	ALL ICU COVID-19 Positive patients are recommended for category B Anticoagulation to prevent thrombosis Inless contraindication. Go to the anticoagulation orderset and place anticoagulation orders as appropriate. A D-Dimer is recommended to assist with anticoagulation decisions. If the patient has NOT had a recent D-Dimer, order a D-Dimer from the Anticoagulation set. (BPA #) Last DDIMER, collected/resulted: DD/MM/YYYY = Result value Last PLT, collected/resulted: DD/MM/YYYY = Result value Last PLT, collected/resulted: DD/MM/YYYY = Result value Last NR, collected/resulted: DD/MM/YYYY = Result value Copen Order Set Do Not Open COVID-19 Anticoagulation ADULT Preview Acknowledge Reason Already on appropriate anticoagulation Anticoagulation Contraindicated Not provider managing anticoagulation © 2020 Epic Systems Corporation Image: Accept Digmiss
© 2020 Epic Systems Corporation	Interruptive Alert Logic
	Criteria

ogic	ND NOT 7) AND NOT 1 AND 2 AND 3 AND 4 AND NOT 6	📥 Logic Helper
		<i>, ,</i>
7	CL PATIENT HAS COVID-19 RECOVERED STATUS [6628]	0
6	IP RX PATIENT ON ENOXAPARIN DOSE GREATER THAN 40 MG CRITERIA [6518]	~
5	CL COVID INFECTION PRESENT [6355]	~
4	CL PATIENT IS NOT ON HEPARIN / ARGATROBAN INFUSIONS [6214]	~
3	CL ADT STATUS IS ICU [6213]	~
2	CL PATIENT HAS BEEN ADMITTED MORE THAN 8 HOURS [6212]	~
1	CL PLATELETS < 30 [6208]	~

© 2020 Epic Systems Corporation

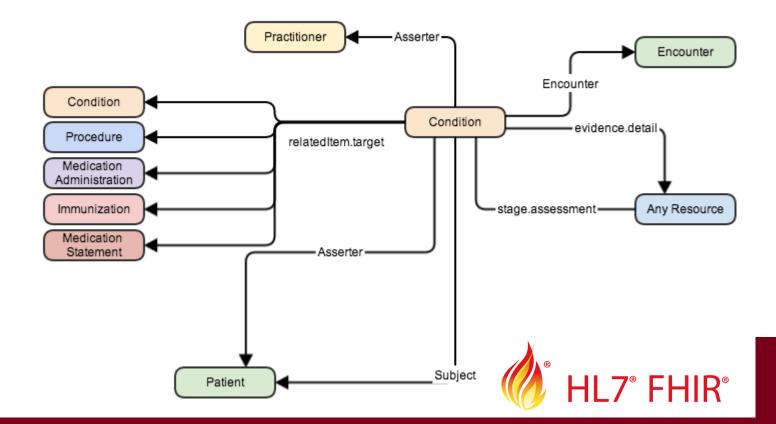
Rib Fracture Clinical Decision Support Care Map

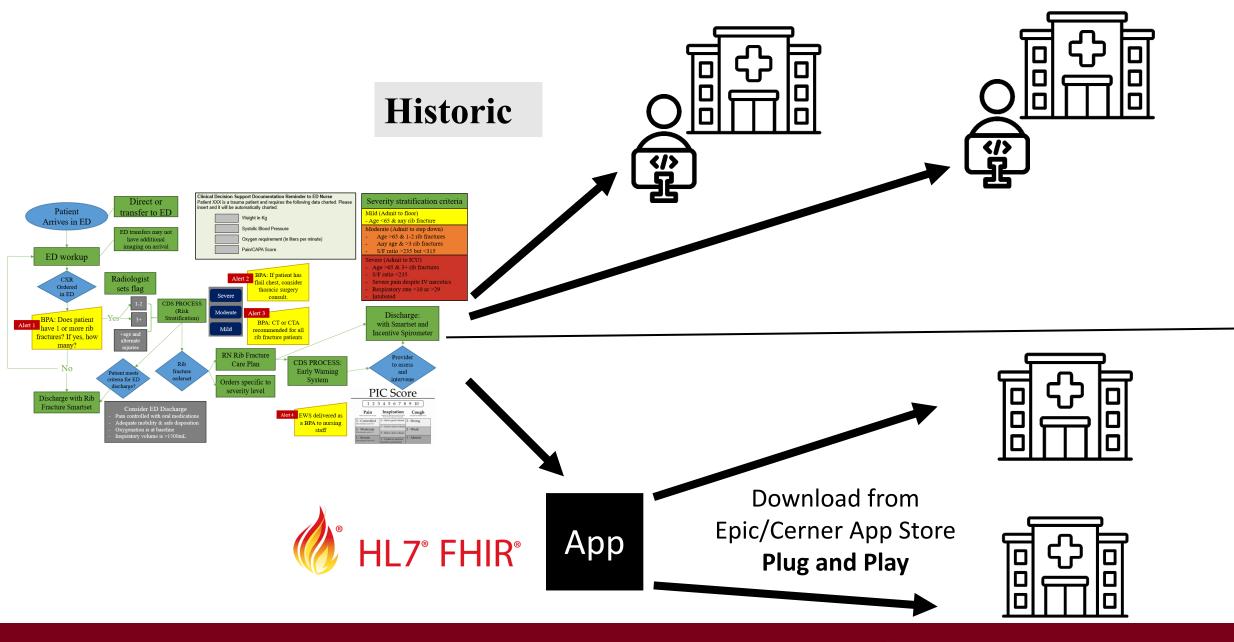


Problem with these examples of decision support shown which are commonplace:

- 1.) **INTEROPERABILITY** Institution and EHR (i.e. Epic, Cerner)- specific
- 2.) MANUALLY INTENSIVE Each institution to build and deploy, not computable, not plug and play
- 3.) Usability (UI/UX) nightmare

HL7 FHIR allows a standardized interoperable set of rules to exchange electronic healthcare data

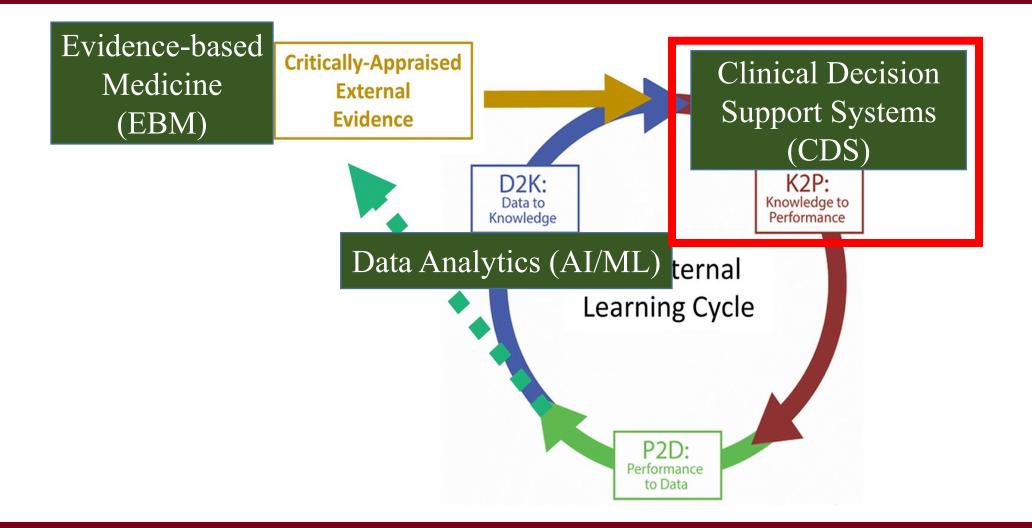






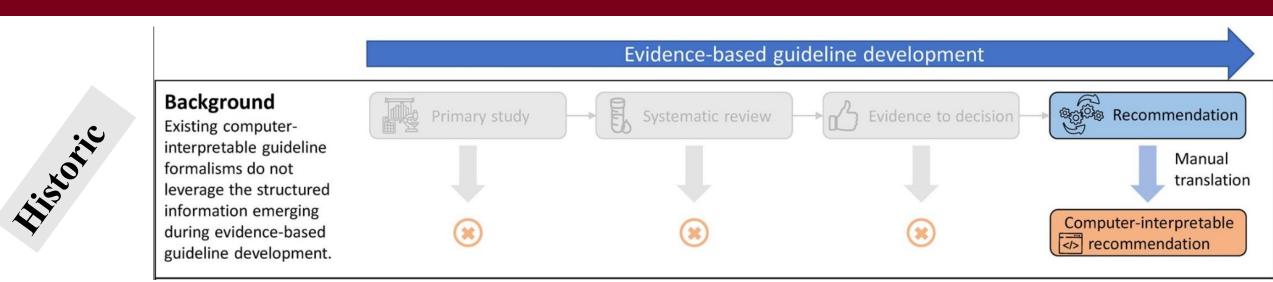
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The Learning Health System integrates three disciplines: EBM + AI/ML + CDS





Evidence-based Medicine as a discipline is undergoing major transformation



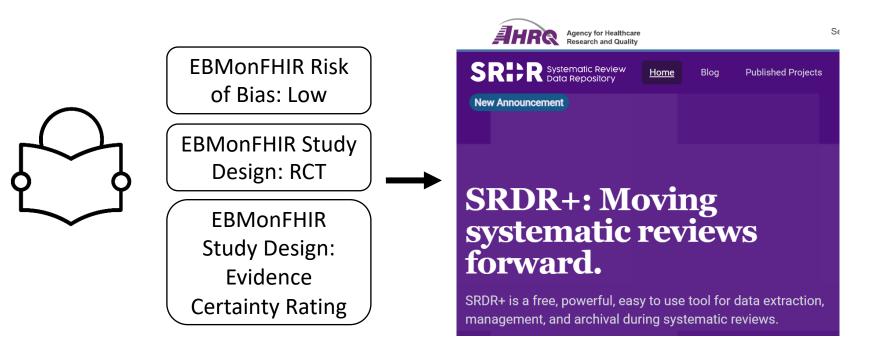
- A society or group conducts a systematic review
- A guideline committee generates guidance and an 41 page narrative PDF guideline is written
- Each health system then has their local experts interpret that guideline and create a set of rules/algorithm
- Each health system's IT team then builds that natively into their EHR as decision support
- 5-10 years later that society updates their guideline and the process repeats

DOI: 10.1002/jpen.2267	¢.
CLINICAL GUIDELINES	

Guidelines for the provision of nutrition support therapy in the adult critically ill patient: The American Society for Parenteral and Enteral Nutrition

Charlene Compher PhD, RD ¹ 💿 🕴 Angela L. Bingham Ph	armD ^{2,3} 💿 Michele McCall MSc,
RD ⁴ Jayshil Patel MD ⁵ Todd W. Rice MD, MSc ⁶	Carol Braunschweig PhD ⁷
Liam McKeever PhD, RDN ⁷ 💿	

EBMonFHIR developing standards for sharing systematic review data such as citation, study design, outcome definitions, risk of bias, certainty of evidence



Imagine how easy systematic reviews, metaanalyses, and annual updates to guidelines would be if every published paper had their attributes already stored in SRDR+

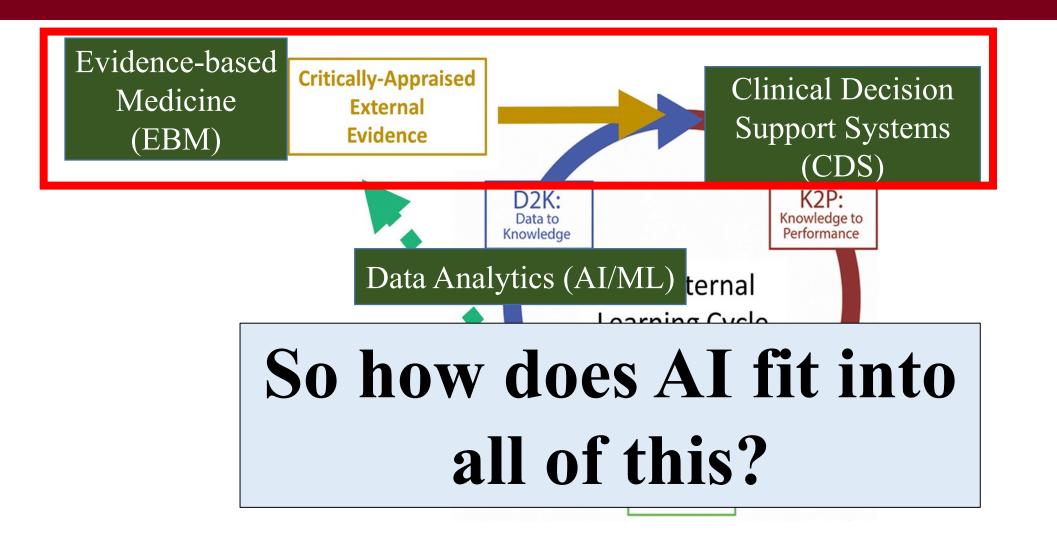


Evidence-based Medicine as a discipline is undergoing major transformation

Knowledge Level	Description	Example
L1	Narrative	Guideline for a specific disease that may be written in the format of a peer- reviewed journal article
L2	Semi- structured	Flow diagram, decision tree, or other similar format that EXPLICITLY describes or expresses logic constructs that are interpretable by non-SME 'computable logic developer' for constructing L3, BUT are also expressed in a manner sufficient for domain SME to review and validate
L3	Structured	Standards-compliant Specification for CDS that explicitly encodes computer interpretable logic including data model(s), terminologies (concepts, value sets), logic expressions in a computable language sufficient for implementation- often across a broader set of local implementations
L4	Executable	Manifestation of the logic (typically in a user interface) that is used in a local execution environment (e.g. CDS interventions running live in a local production EHR environment) or available via web services



The Learning Health System integrates three disciplines: EBM + AI/ML + CDS

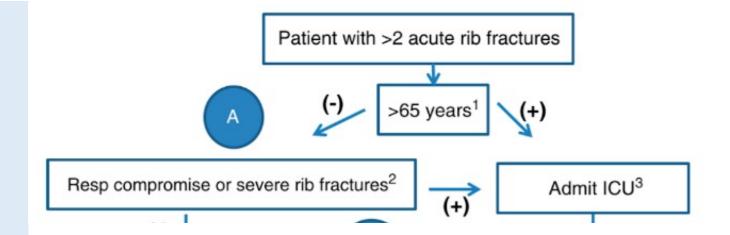




Lets go back to our rib fracture treatment algorithm

Current State

One size fits all

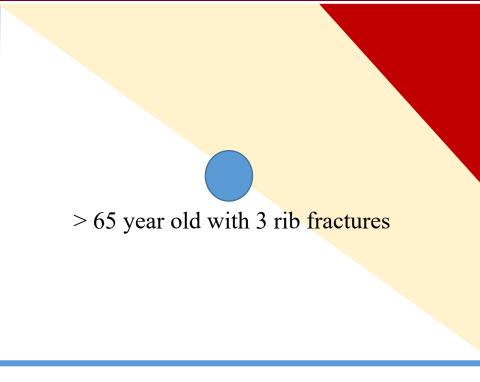


Best practice for rib fracture patients age 66 and older with 3 or more rib fractures is admission to the ICU



AI/ML allows us to generate a patient specific probability that a treatment is beneficial. RCTs can then investigate if AI (personalized) outperforms current Std of Care

Number of Rib Fractures

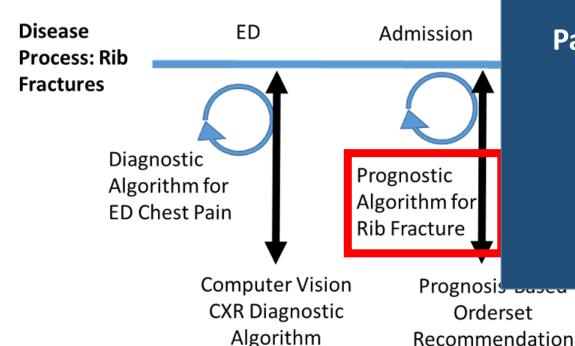


Don't forget additional dimensions: What if they are a smoker with empysema? What if they are on home oxygen? What if they have a collapsed lung? Do X-ray findings/features inform treatment?

Age



Integration of AI tools into the Rib Fracture Care Map



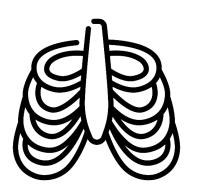
Example Clinical Decision Support BPA

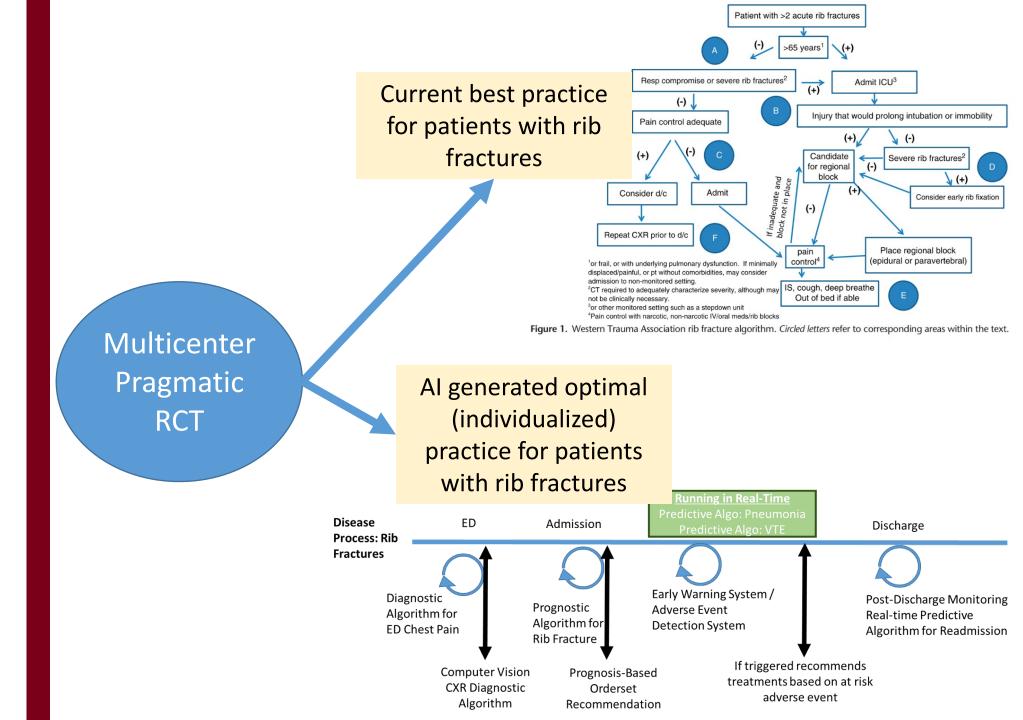
Your patient has a rib fracture

Patient's probability of mortality <u>without ICU</u> <u>admission</u> = 11% (95% CI 9% - 15%)

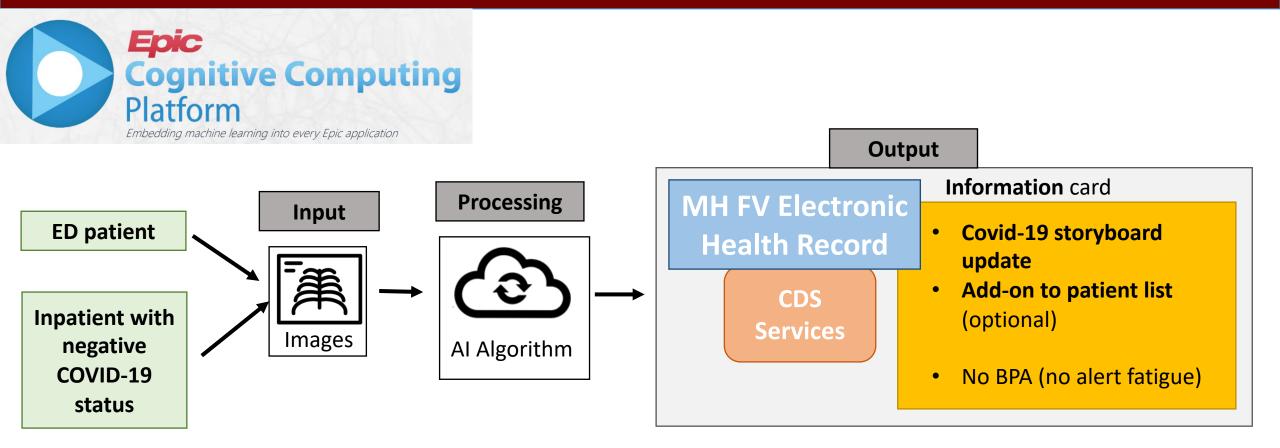
Patient's probability of mortality <u>with ICU</u> <u>admission</u> = 4% (95% CI 2%-6%)

> treatments based on at risk adverse event



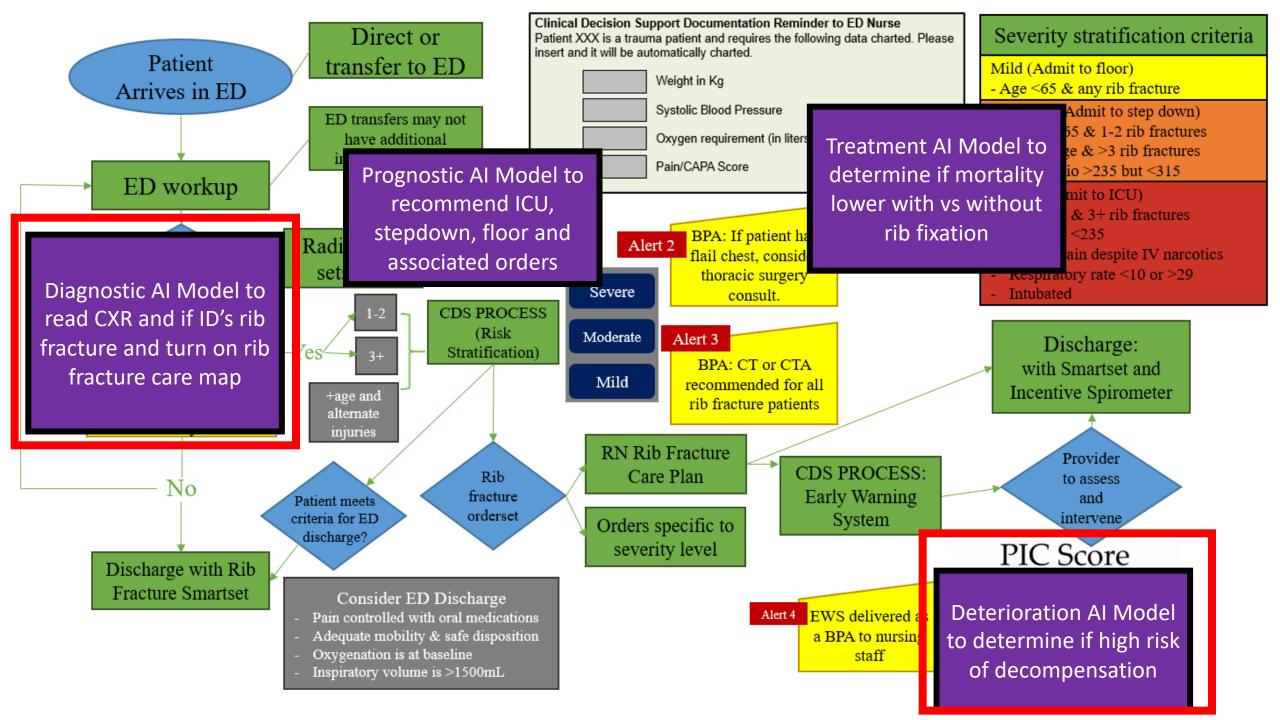


These algorithms can then become integrated into CDS systems



Occurs in REAL-TIME

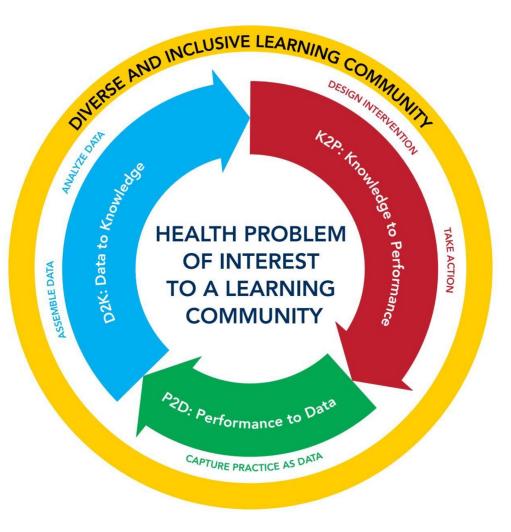




How do we as a trauma community achieve

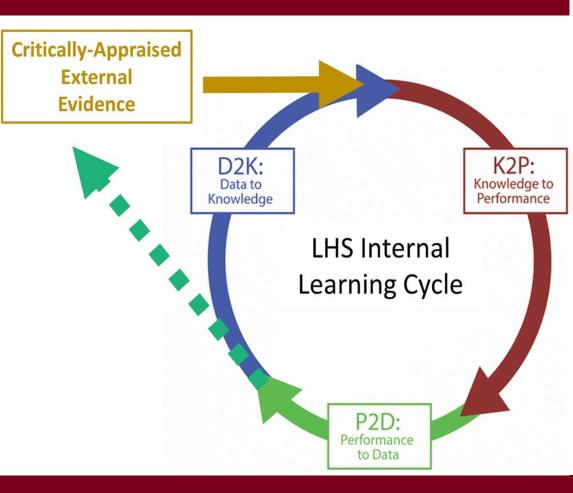
"...a health system in which internal data and experience are systematically integrated with external evidence, and that knowledge is put into practice."

- Agency for Healthcare Research and Quality



Learning Health NETWORK

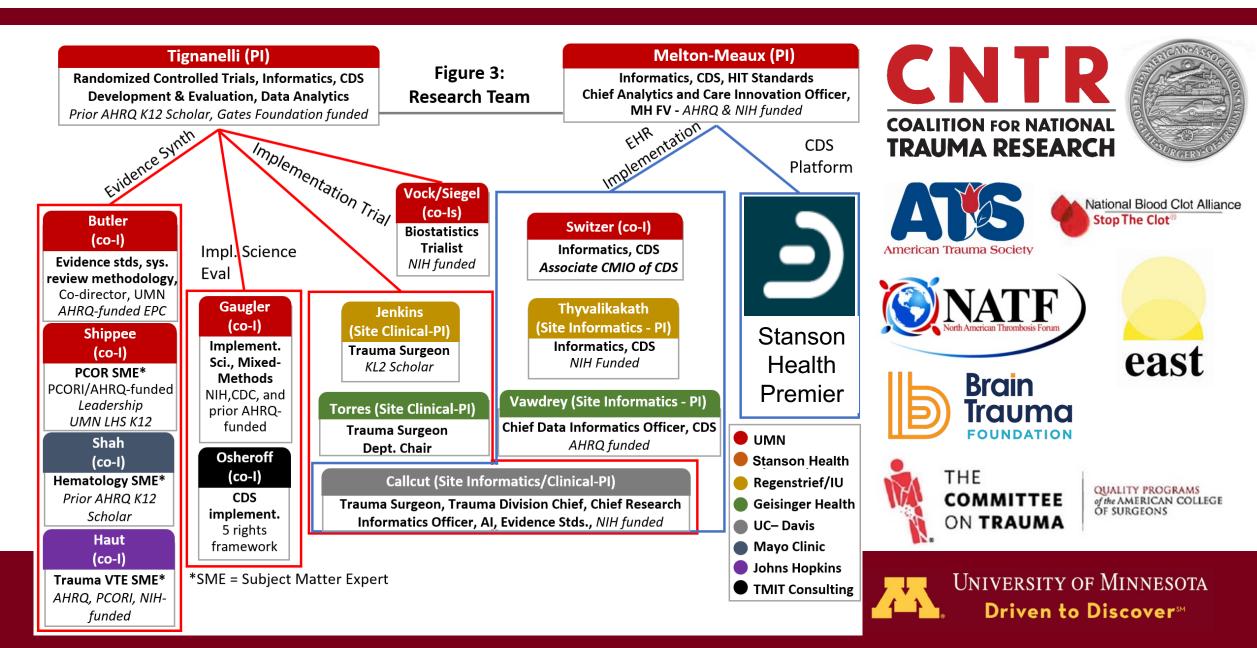
- UMN was recently rewarded an AHRQ R18 grant to develop such a Learning Health Network for Trauma (PI: Tignanelli / Melton-Meaux)
- Need 3 key pieces to make a LHN
 - 1.) Centrally Maintained Clinical Decision Support Applications
 - 2.) Process for Evidence-Maintenance
 - 3.) Shared Real-time Data Repository to enable AI



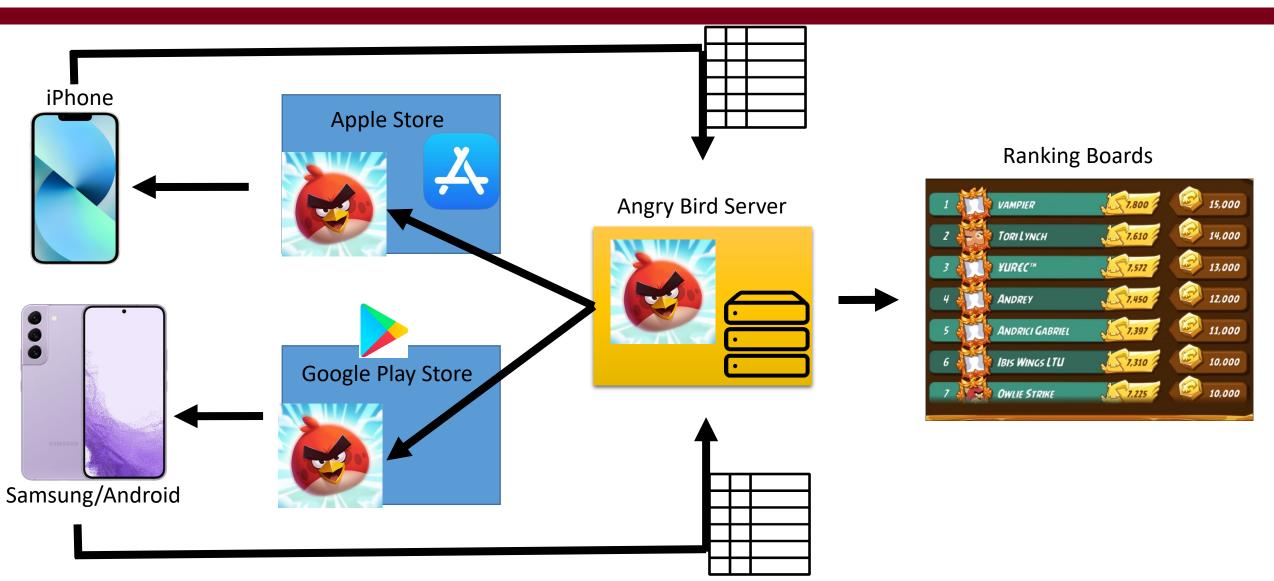
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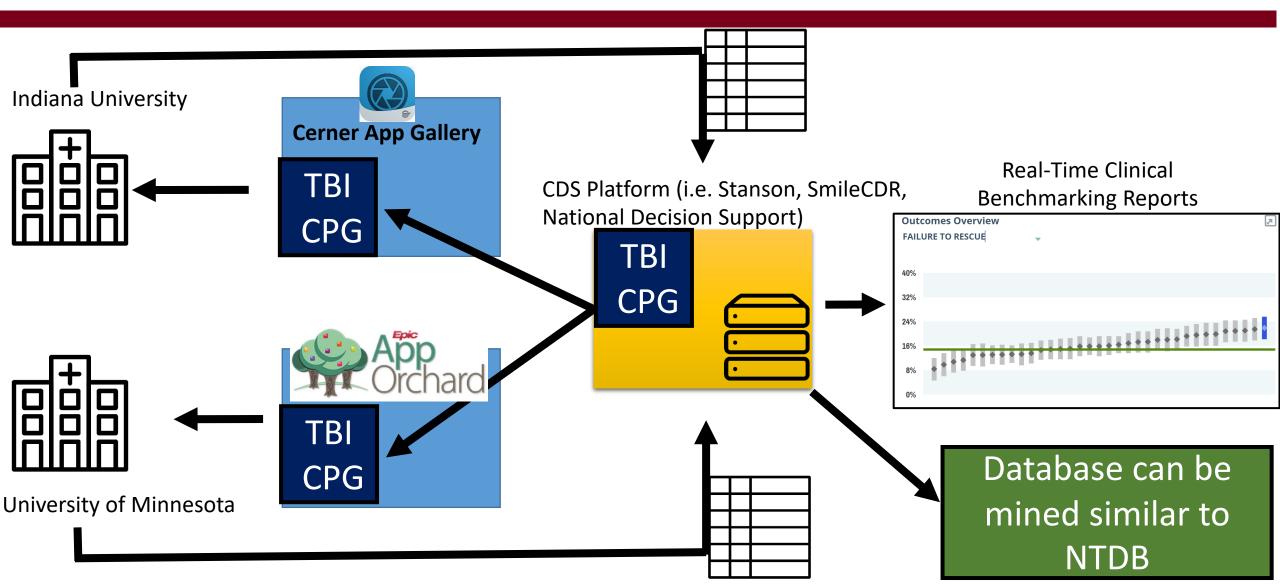
The Trauma Learning Health Network Team



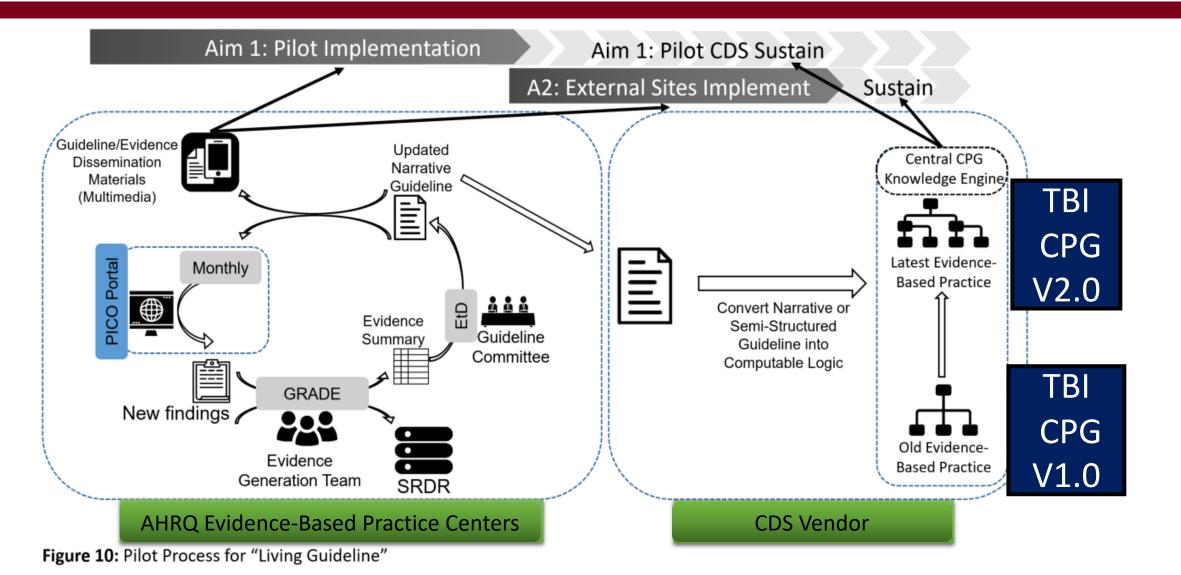
Centralized Decision Support Application – an example from Angry Birds



Well now imagine if the "Angry Birds" Application was a Clinical Care Map for TBI Management



If the evidence or best practice changes, can update the application once centrally and push out update



Developed a data infrastructure since 2020 to support "AI/Analysis-Ready Datamarts"

Health System EHR

Data

> 4.6 million M Health Fairview Epic since 2011

Intraoperative and **Procedural Videos** Operative Videos!

- ✤ 7 PB of images
- ✤ 0.6 billion clinical notes
- ✤ + ECG, EEG, pathology, and other notes

ECG images

Device Robotic Neurosurgical NPWT (i.e. Abthera) **Manual Disease** Registries NAACR (Cancer) TQIP (Trauma) NSQIP (Surgery) GWTG (Stroke) Etc...

Device Data

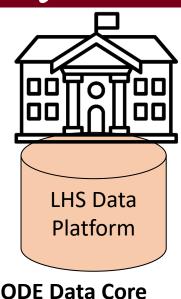
Staplers

*

*

*

Ventricular Assist



CQODE Data Core

2 Directors 1 Administrator 2 Project Managers 1 Regulatory Specialist **1.0 FTE Solutions Architect** 8.5 FTE Data Analysts 3.0 FTE ETL 2.0 FTE SQL Analysts Over 20 Clinicians assisting

Omics Data

Proteomic, Transcriptomic, Metabolomic, Cell Surface Markers, Immunologic



Death Certificate Database Immunization Database Well Water Database Wastewater Database Radon Database **Environmental / Pollution Data:** EPA, ERS, CACES Databases *



Social Determinants of Health ✤ 11 SDoH

- Gender Identity
- Sexual Orientation



Bluetooth Home Scales Bluetooth Home Spirometers Patient Mobile Applications

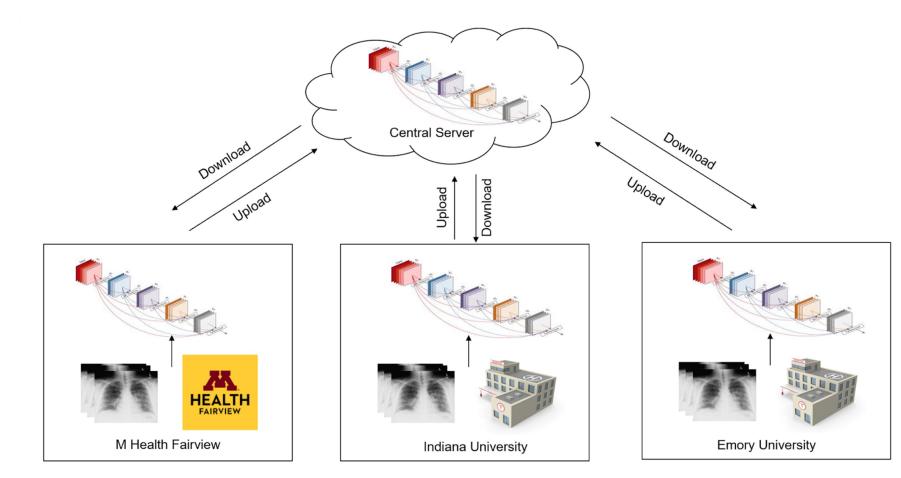
"US Healthcare Federated Learning Collaborative" – Founded in 2020

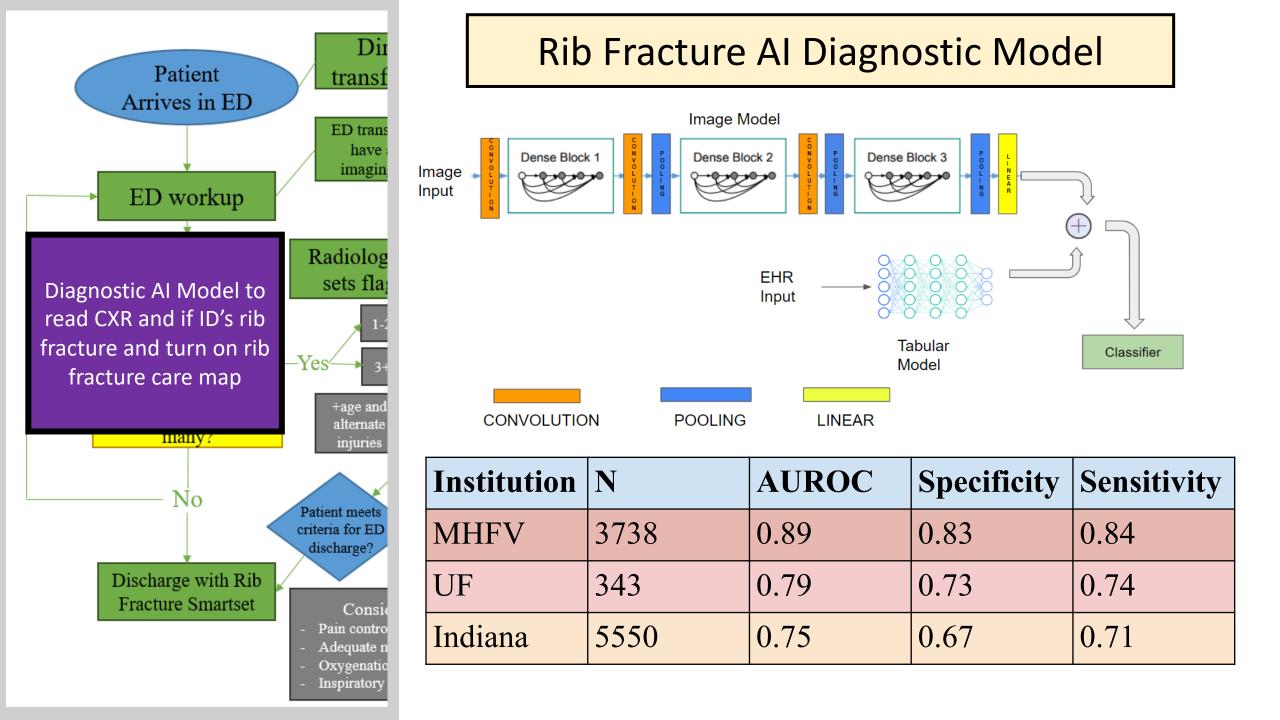
Federated partners

- 1. M Health Fairview
- 2. Indiana University
- 3. Emory University
- 4. University of Florida Gainesville
- 5. Medical University of Carolina (In Progress)
- University of North Carolina (UNC) (In Progress)

Corporate Partners:

- CISCO
- Nvidia
- Microsoft AI for Health





In conclusion, to enable the future digital transformation of trauma evidencebased practice

- Current medical practice routinely fails to delivery evidence-based care
- Technological advances can expedite the evidence to guidance process in a more efficient, computational, and interoperable manner
- Al can enable personalized care and be readily integrated into decision support systems
 - But AI requires new methods for data management

We need to partner together to do this as a medical discipline ideally as a **<u>pilot</u>** across 5-6 trauma systems in conjunction with medical societies, decision support vendors, and the tech industry with financial support from the ACS

We can serve as a model for the entire field of medicine

The Learning Health System integrates three disciplines: EBM + AI/ML + CDS

