ebhc CONFERENCE 2026

THE ECOSYSTEM OF EVIDENCE

Navigating the future
of the ecosystem of evidence

Artificial intelligence and digital transformation
in research and healthcare

11th EBHC International Conference
Taormina, 21st – 24th October 2026

#EBHC2026

30th 1996-2026 GIMBE EVIDENCE FOR HEALTH

International Society for Evidence-Based Health Care

A Deep Learning Artificial Intelligence Diagnostic Model for Adult Rib Fractures across 35 U.S. Hospitals to improve activation of a best practice clinical care pathway for patients with rib trauma

Christopher Tignanelli, MD MBA MS FACS FAMIA
Associate Professor of Surgery
Scientific Director for UMN's Program for Clinical AI

Background

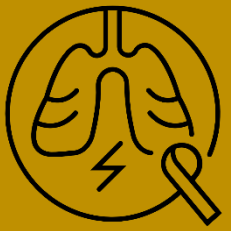
Why care about rib fractures?

Trauma
4th leading cause death in U.S.

66% of patients with chest trauma



45-48%



22% (> 60 yo)
11% (< 60 yo)



55% of patients > 60 who die from chest trauma have **no injury** worse than rib fractures

34% -> LTACH

Evidence-based practices are still not mainstream for patients with traumatic rib fractures

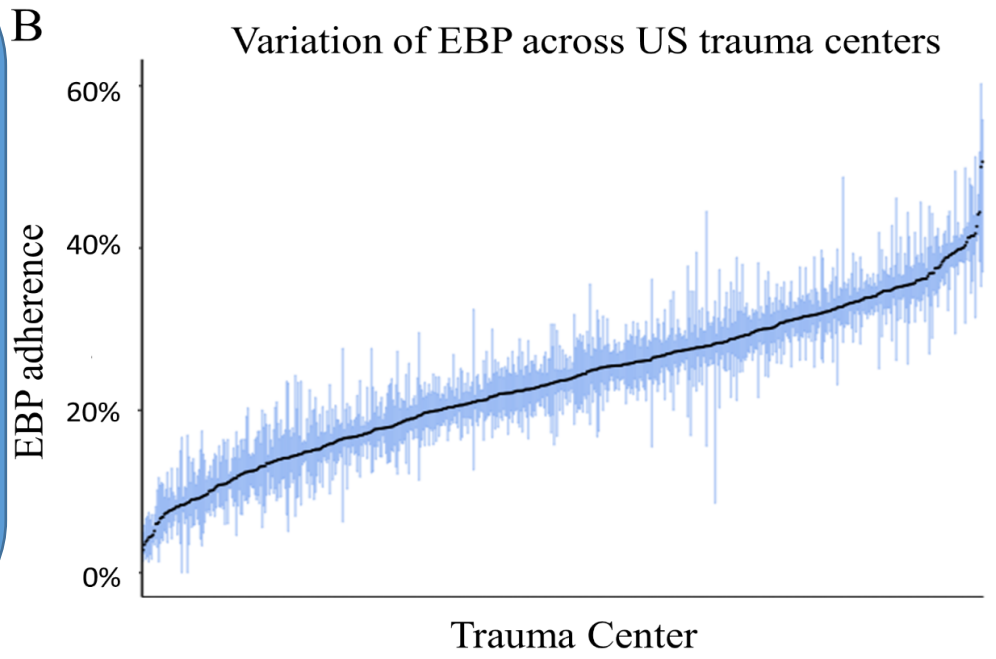
For patients 65 yrs older with > 2 rib fractures:

EBP1: 35% reduced mortality ($p < 0.001$)

EBP2: 7% reduced mortality ($p = 0.02$)

For patients with Flail Chest:

EBP3: 90% reduced mortality ($p < 0.001$)



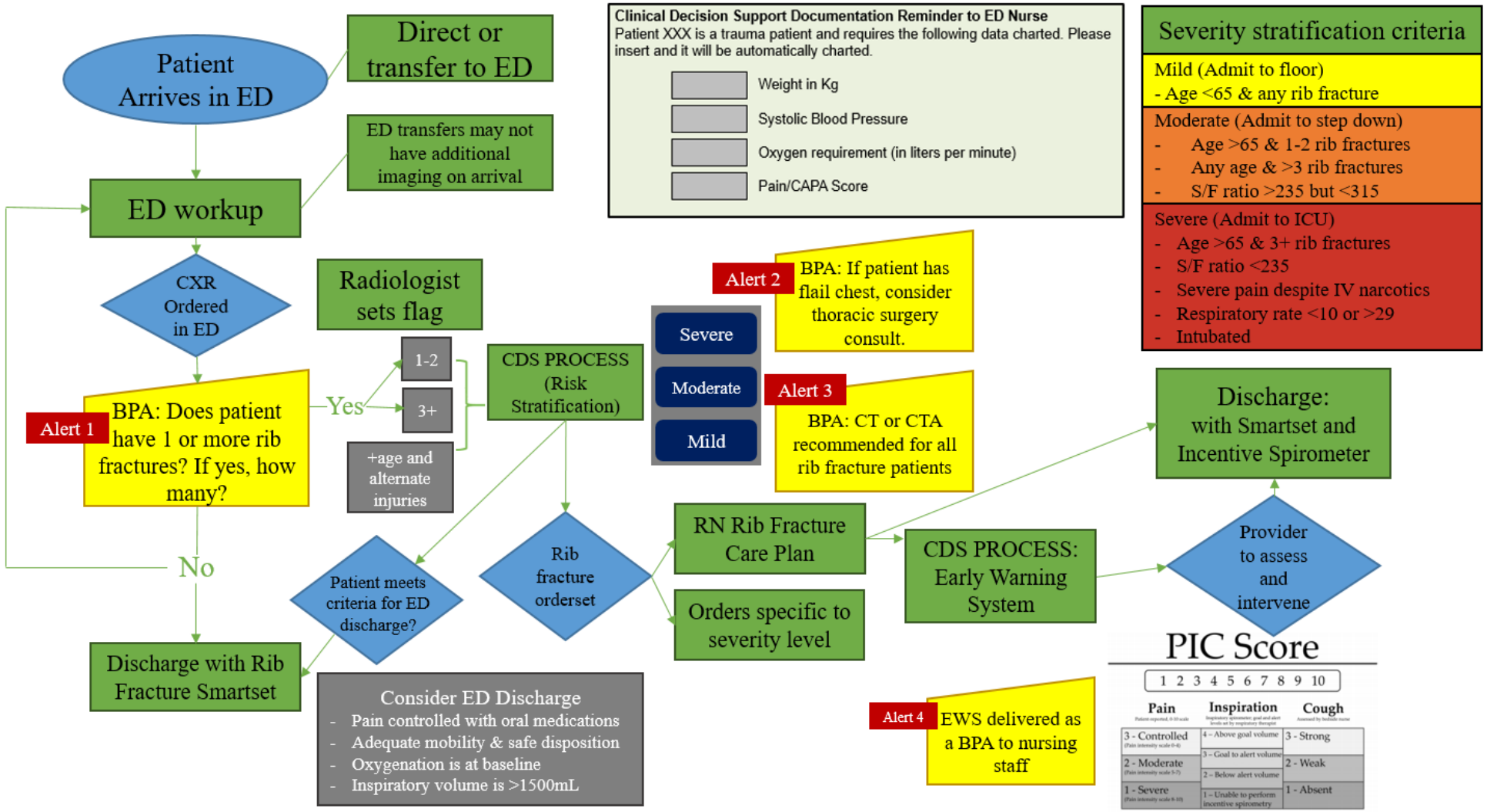
	Percentage	Received / Eligible
EBP1	4%	4,578 of 111,589
EBP2	42%	46,456 of 111,589
EBP3	14%	3,302 of 24,319
EBP4	1%	1,240 of 111,589
EBP5	42%	109,160 of 258,334
EBP6	40%	32,405 of 81,417

Original Investigation | Surgery

Association Between Adherence to Evidence-Based Practices for Treatment of Patients With Traumatic Rib Fractures and Mortality Rates Among US Trauma Centers

Christopher J. Tignanelli, MD[1,2,3]; Alexander Rix, MS[3]; Lena M. Napolitano, MD[4]; Mark R. Hemmila, MD[4]; Sisi Ma, PhD[3]; Erich Kummerfeld, PhD[3]

Evidence-Based decision support care map built into Epic EHR



Implementation

- 10 hospitals
- Graduated roll-out starting 11/2020
- Provider education by providers
  - Virtual provider training session: ED providers, trauma, internal medicine
  - Booster training session with updates including GWL
  - Tip sheet
- RN education via online learning module
- RT education by RT
- Booster education sessions
- Audit and Feedback
  - Reach and Adoption (Hospital-level, Nursing unit-level, and Provider-level) tracked daily using Microsoft PowerBI

Conducted a casual propensity-matched analysis

AAST PODIUM 2022

Check for updates

A novel, evidence-based, comprehensive clinical decision support system improves outcomes for patients with traumatic rib fractures

Emma K. Jones, Ivana Ninkovic, Matthew Bahr, Sarah Dodge, Michael Doering, David Martin, Julie Ottosen, Tadashi Allen, Genevieve B. Melton, Christopher J. Tignanelli

Authors and Affiliations >

Journal of Trauma and Acute Care Surgery 95(2):p 161-171, August 2023. | **DOI:**

Identified:

85% reduction in unplanned ICU transfer (propensity matched) (p = <0.001)
40% reduction in 1 year mortality (Cox PH regression) (p = 0.01)
(trend) 50% reduction in need for mechanical ventilation (propensity matched) (p = 0.15)
13% reduction in hospital LOS (Poisson regression) (p = 0.019)

Process:

Higher rate of adherence with the NEXUS Chest CT Criteria (80.8% vs 61.1%, p < 0.001)
Lower first 24 hr Morphine equivalents (32.5 vs 42.75 mg, p< 0.001)
High rate of anesthesia consultation for epidural (23.7% vs 8.4%, p < 0.001)

Key issue: Only 45% of the time the decision support system was used

Aims

If a patient arrives in the ED and receives a chest x-ray can an AI-enabled CDS system predict if the patient has a rib fracture?

Investigate

Prospective multi-hospital observational study to develop and evaluate a diagnostic AI model for rib fractures

UFHealth
UNIVERSITY OF FLORIDA HEALTH

1 hospital

UNC HEALTH

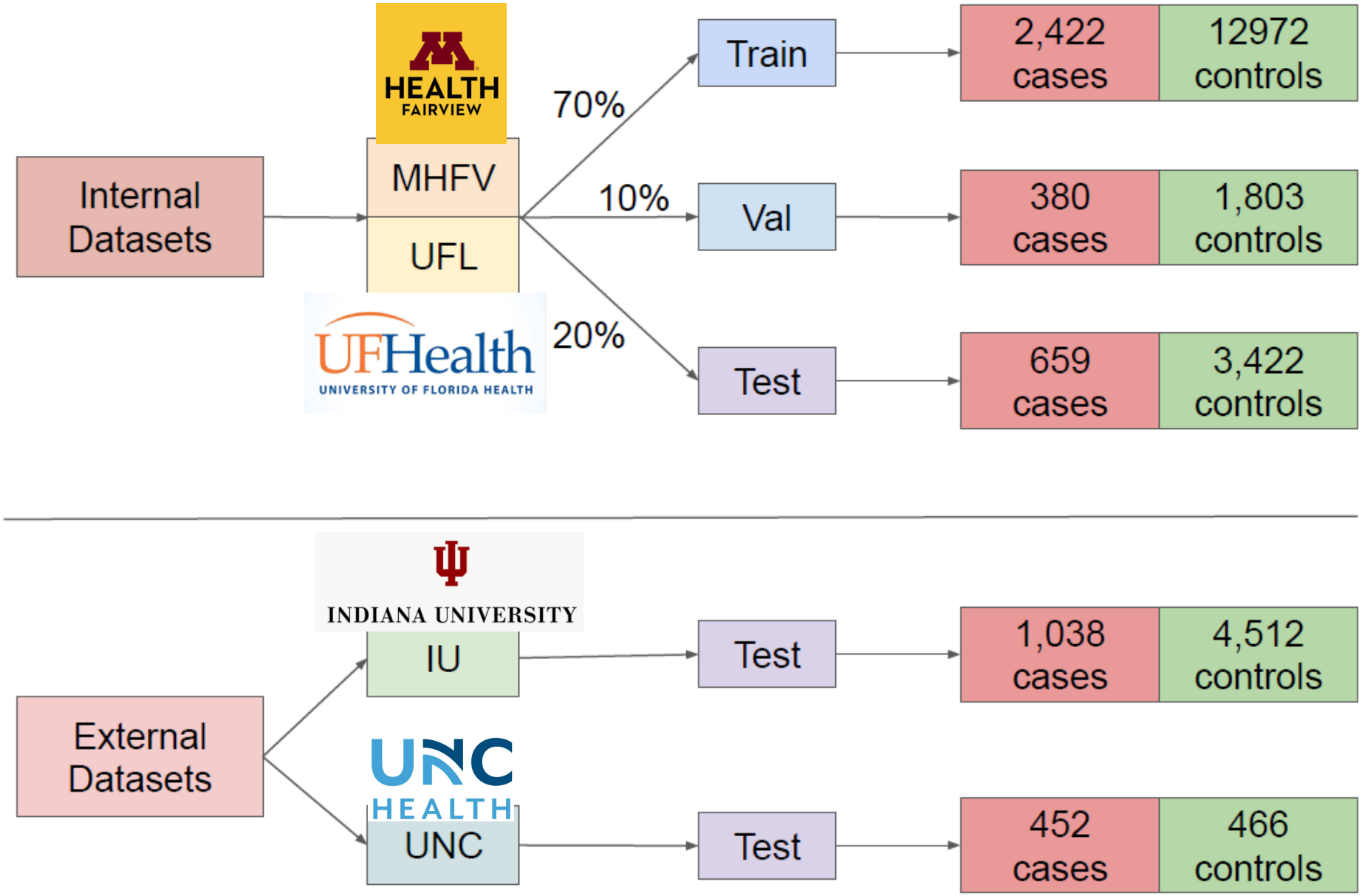
8 hospitals

HEALTH FAIRVIEW

10 hospitals

INDIANA UNIVERSITY

16 hospitals


Internal Datasets
MHFV
UFL
70%
10%
20%
Train
Val
Test
2,422 cases
12972 controls
380 cases
1,803 controls
659 cases
3,422 controls
External Datasets
IU
UNC
Test
Test
1,038 cases
4,512 controls
452 cases
466 controls

Methods

Multi-Modal Model Development

EHR elements in model:

BMI, Co2, Creatinine, Hgb, Plts, HR, RR, SBP, Troponin, WBC, Reason for Visit, DBP, Temp, Respiratory level (ordinal room air, facemask, PPV, Intubated), 02 Sat FI02, Age, Pain

Multimodal means EHR elements + CXR image

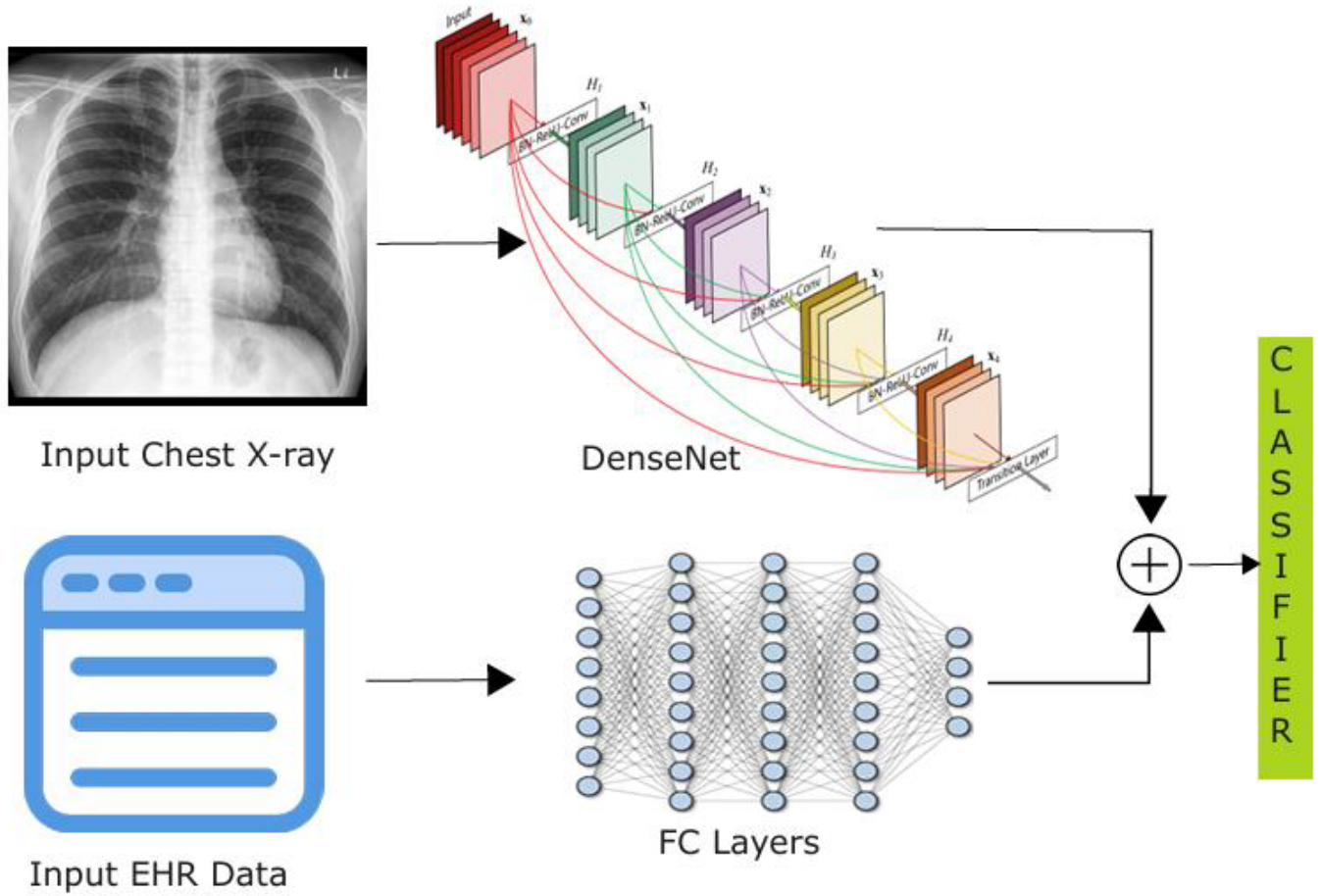
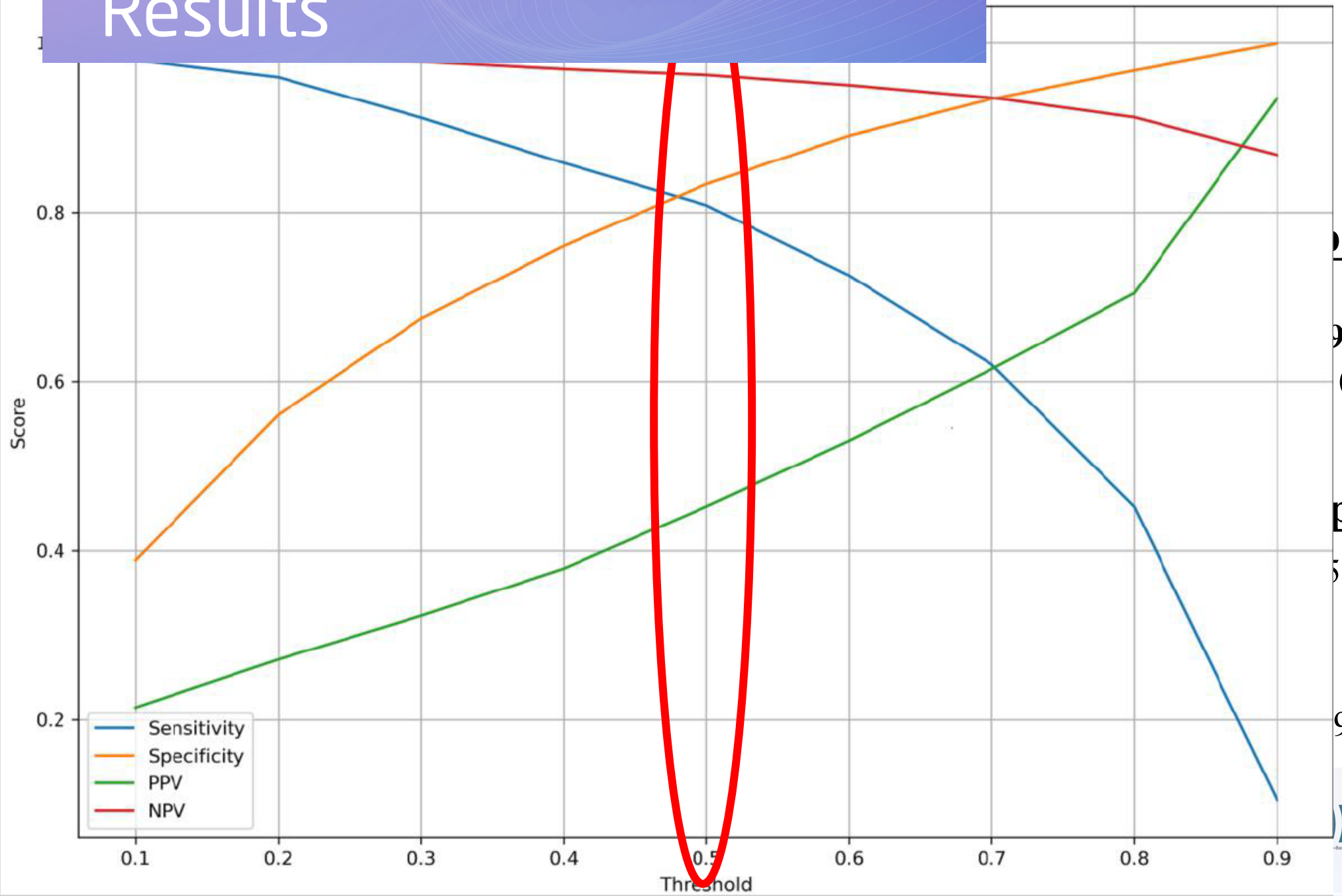


Figure 1. Overview of the rib fracture classification AI deep learning pipeline. DenseNet-121 (image model) receives the input as chest x-ray and the fully connected (FC) layers (tabular model) receives input as electronic health record (EHR) data. The output features from both the image model and tabular model are then concatenated to pass through the final classification layer.

Results



ective Validation

90 (95% CI 0.88-0.91)
(95% CI 0.74-0.85)

pective Validation

5% CI, 0.73-0.76)

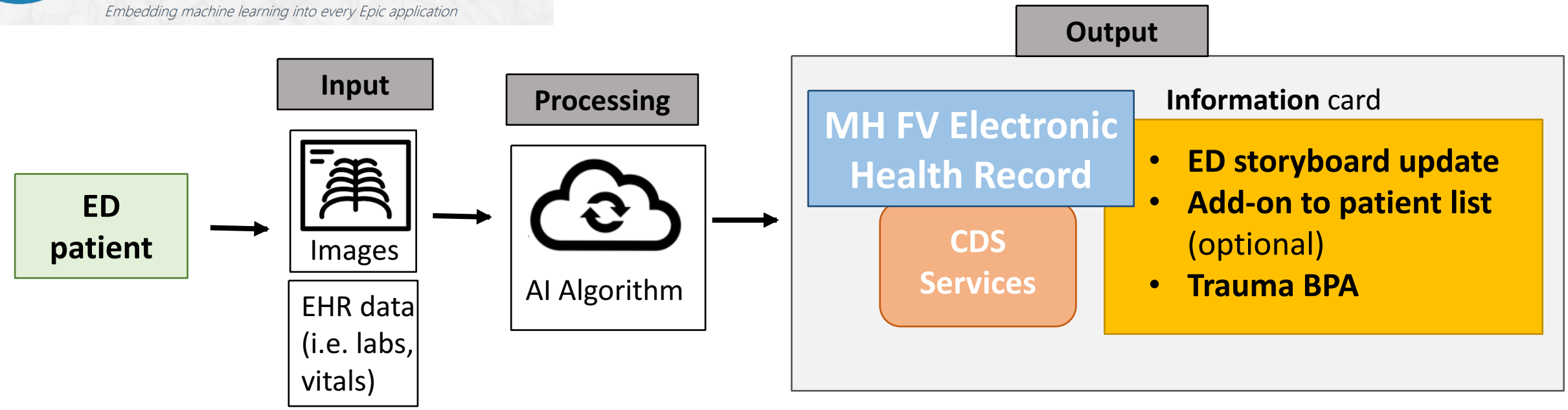
95% CI, 0.67-0.73)

30th GIMBE 1996-2026 EVIDENCE FOR HEALTH

Deep Learning AI algorithms can be directly deployed into EHR

Epic Cognitive Computing Platform

Embedding machine learning into every Epic application



Occurs in REAL-TIME

Real World – "Live" Performance Pilot

Prediction Timeline & Model Performance

Leveraging early ED data to predict risk — when it's best for the patient.



1. Early Prediction (0–3 Hours)

Model makes a prediction using data available within the first 3 hours of ED arrival.

Model Performance (0–3 hr)

AUROC 0.734

(95% CI 0.68 – 0.79)

2. 2–3 Hour Prediction

Model waits for hours 2–3 of ED data before making a prediction.

Model Performance (2–3 hr)

AUROC 0.7504

(95% CI 0.66-0.84)

3. Full 3-Hour Prediction

Model uses the full 3 hours of data and only makes a prediction at 3 hours (or later).

Model Performance (3 hr)

AUROC 0.824

(95% CI 0.76 - 0.89)

Limits

- Real World “Silent” Validation only had 53 cases
- Multimodal analytic techniques have improved over the past few years
- How to handle a 50% false positive rate with a live deployment?
- Real World Validation was only done at one site (the site with the best retrospective performance)

Conclusions and Next Steps

- Developed a model that performs with good performance in real world environments with AUROC 0.824
- Determine optimal window for AI Diagnostic Decision Support deployment including optimal threshold
- Evaluation as an IRB approved prospective observational research study
- Primary Implementation Outcome: Activation rate (%) of Rib Fracture Evidence-Based Decision Support Pathway