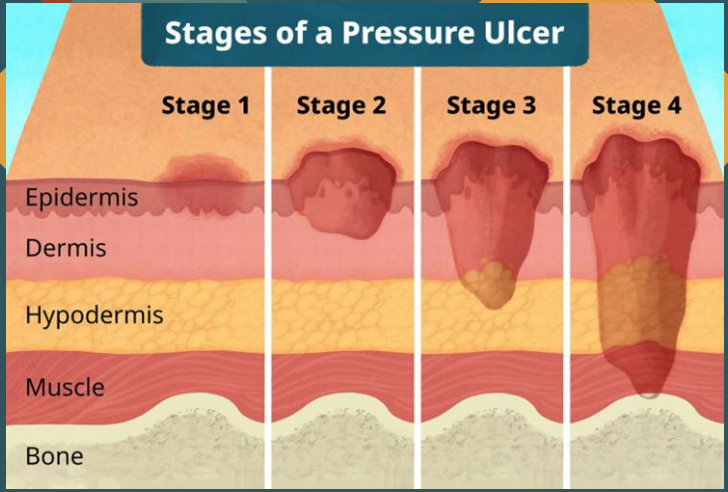
BEYOND BRADEN: DATA-DRIVEN PREDICTION AND PREVENTION OF HAPIS

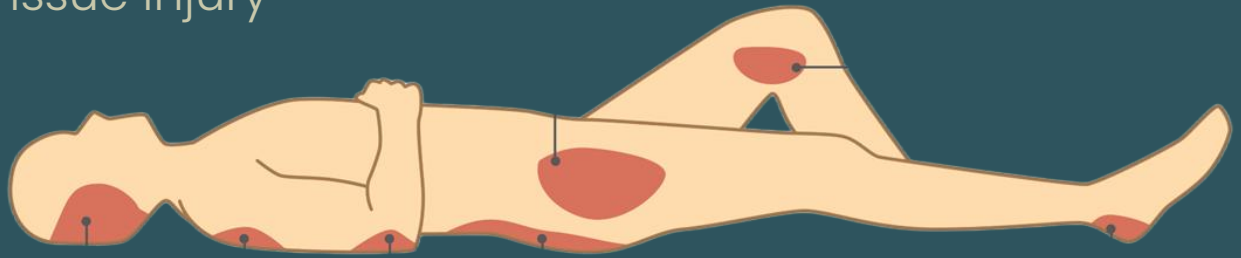
A Multimodal Clinical Decision Support System Using MIMIC-IV

Andrea Wroblewski
Group 1

What is a HAPI?

- Hospital Acquired Pressure Injury
  - Any pressure injury that develops after hospital admission
- Pressure Injury/Ulcer
  - Stage 1-4
  - Unstageable
  - Deep Tissue Injury





Why HAPIs?

The Burden:

HAPIs affect ~2.5 million US patients annually, costing $26 Billion/year.

The Trend:

While superficial injuries are declining, Severe Injuries (Stage 3, 4, DTI) remain stagnant.

The Gap:

Current prevention efforts are failing to catch the most dangerous cases in the ICU.

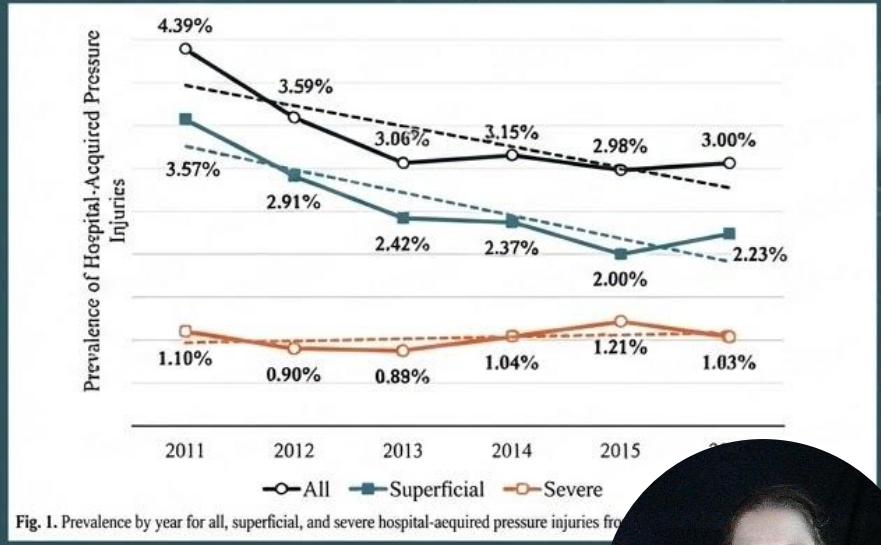
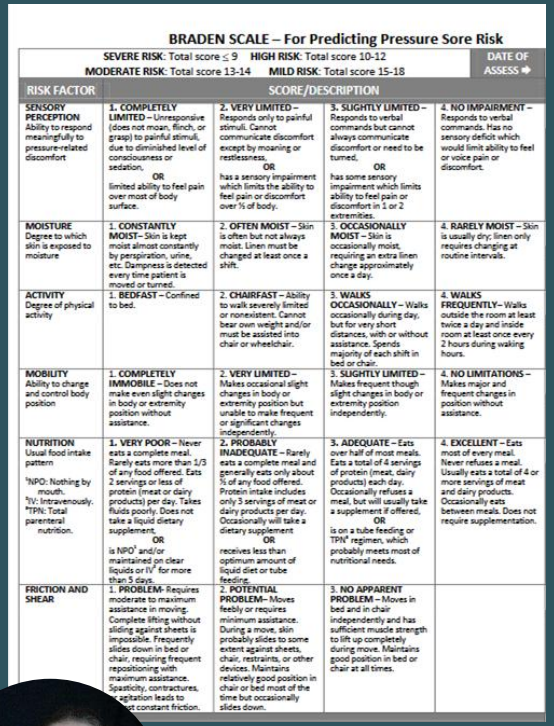


Fig. 1. Prevalence by year for all, superficial, and severe hospital-aequired pressure injuries fr

Limitations of Current Tools: The Braden Scale



BRADEN SCALE – For Predicting Pressure Sore Risk

SEVERE RISK: Total score ≤ 9 **HIGH RISK**: Total score 10-12
MODERATE RISK: Total score 13-14 **MILD RISK**: Total score 15-18
DATE OF ASSESS ➡

RISK FACTOR	SCORE/DESCRIPTION			
SENSORY PERCEPTION Ability to respond meaningfully to pressure-related discomfort	**1. COMPLETELY LIMITED** – Unresponsive (does not moan, flinch, or grasp) to painful stimuli, due to diminished level of consciousness or sedation, OR limited ability to feel pain over most of body surface.	**2. VERY LIMITED** – Responds only to painful stimuli. Cannot communicate discomfort except by moaning or restlessness, OR has a sensory impairment which limits the ability to feel pain or discomfort over ½ of body.	**3. SLIGHTLY LIMITED** – Responds to verbal commands but cannot always communicate discomfort or need to be turned, OR has some sensory impairment which limits ability to feel pain or discomfort in 1 or 2 extremities.	**4. NO IMPAIRMENT** – Responds to verbal commands. Has no sensory deficit which would limit ability to feel or voice pain or discomfort.
MOISTURE Degree to which skin is exposed to moisture	**1. CONSTANTLY MOIST**– Skin is kept moist almost constantly by perspiration, urine, etc. Dampness is detected every time patient is moved or turned.	**2. OFTEN MOIST** – Skin is often but not always moist. Linen must be changed at least once a shift.	**3. OCCASIONALLY MOIST** – Skin is occasionally moist, requiring an extra linen change approximately once a day.	**4. RARELY MOIST** – Skin is usually dry; linen only requires changing at routine intervals.
ACTIVITY Degree of physical activity	**1. BEDFAST** – Confined to bed.	**2. CHAIRFAST** – Ability to walk severely limited or nonexistent. Cannot bear own weight and/or must be assisted into chair or wheelchair.	**3. WALKS OCCASIONALLY** – Walks occasionally during day, but for very short distances, with or without assistance. Spends majority of each shift in bed or chair.	**4. WALKS FREQUENTLY**– Walks outside the room at least twice a day and inside room at least once every 2 hours during waking hours.
MOBILITY Ability to change and control body position	**1. COMPLETELY IMMOBILE** – Does not make even slight changes in body or extremity position without assistance.	**2. VERY LIMITED** – Makes occasional slight changes in body or extremity position but unable to make frequent or significant changes independently.	**3. SLIGHTLY LIMITED** – Makes frequent though slight changes in body or extremity position independently.	**4. NO LIMITATIONS** – Makes major and frequent changes in position without assistance.
NUTRITION Usual food intake pattern *NPO: Nothing by mouth. *IV: Intravenously. *TPN: Total parenteral nutrition.	**1. VERY POOR** – Never eats a complete meal. Rarely eats more than 1/3 of any food offered. Eats 2 servings or less of protein (meat or dairy products) per day. Takes fluids poorly. Does not take a liquid dietary supplement, OR is NPO* and/or maintained on clear liquids or IV* for more than 5 days.	**2. PROBABLY INADEQUATE** – Rarely eats a complete meal and generally eats only about ½ of any food offered. Protein intake includes only 3 servings of meat or dairy products per day. Occasionally will take a dietary supplement OR receives less than optimum amount of liquid diet or tube feeding.	**3. ADEQUATE** – Eats over half of most meals. Eats a total of 4 servings of protein (meat, dairy products) each day. Occasionally refuses a meal, but will usually take a supplement if offered, OR is on a tube feeding or TPN* regimen, which probably meets most of nutritional needs.	**4. EXCELLENT** – Eats most of every meal. Never refuses a meal. Usually eats a total of 4 or more servings of meat and dairy products. Occasionally eats between meals. Does not require supplementation.
FRICTION AND SHEAR	**1. PROBLEM**- Requires moderate to maximum assistance in moving. Complete lifting without sliding against sheets is impossible. Frequently slides down in bed or chair, requiring frequent repositioning with maximum assistance. Spasticity, contractures, or agitation leads to almost constant friction.	**2. POTENTIAL PROBLEM**– Moves feebly or requires minimum assistance. During a move, skin probably slides to some extent against sheets, chair, restraints, or other devices. Maintains relatively good position in chair or bed most of the time but occasionally slides down.	**3. NO APPARENT PROBLEM** – Moves in bed and in chair independently and has sufficient muscle strength to lift up completely during move. Maintains good position in bed or chair at all times.	

- Moderate predictive validity:
  - false sense of low risk
- Minimal value from certain subscores
- Subjective & inconsistently used by nurses
- HAPI prevalence still high nationally
- Misses physiologic & EHR trends

References:1, 3, 10, 13, & 14

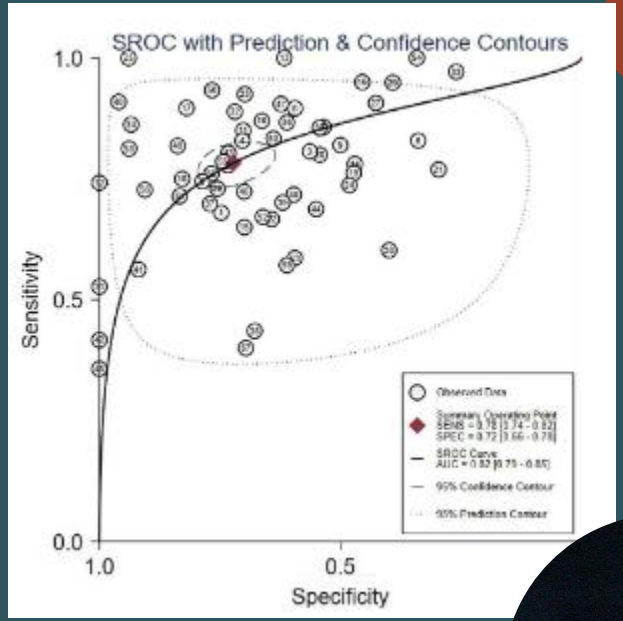
Need for Machine Learning

Why Modern ML Is the Next Step

- Real-time risk
- Uses full EHR (notes + vitals + labs)
- More objective
- Earlier detection
- Personalized care plans

Why Now?

- EHR maturity
- Better clinical documentation
- NLP/ML available
- Prevention is a priority



Implementation

Methodology: Dataset

Dataset Source:

- MIMIC-IV v3.1
- Unit of analysis: Hospital admission (HADM_ID)
- Adult inpatients with available EHR data
- Combined structured + unstructured elements

Data Sources Included:

- Demographics, admissions, length of stay
- Labs, vitals, I/O, procedures
- Medications: EMAR + Prescriptions + POE
- Diagnoses (ICD-9/10), transfers, ICU events
- Clinical notes (NLP extraction of wound-related language)

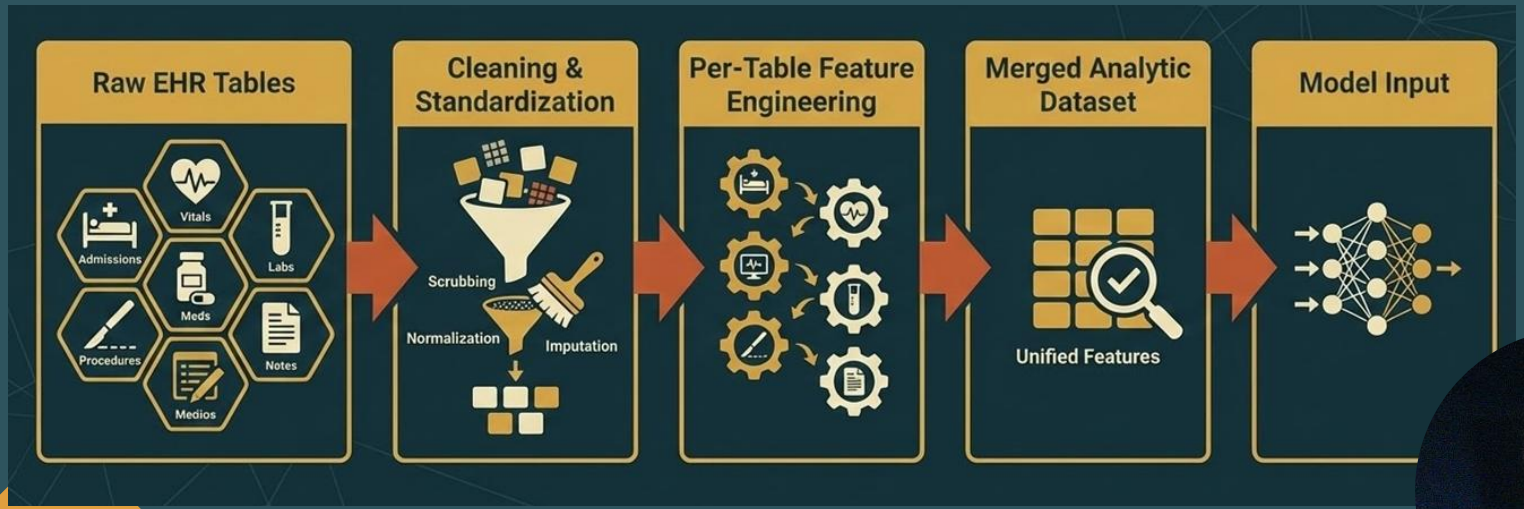
Outcome Label

- HAPI_FINAL = ICD pressure injury codes + NLP-detected wound documentation
- Captures pressure injuries developing after admission

Feature Engineering & Data Processing Pipeline

Extracted raw EHR tables → cleaned → engineered features

Combined vitals, labs, meds, notes, and procedures into one unified dataset



Pipeline Architecture

- Modular domain-specific notebooks
- Clean intermediate feature files
  - *_feat.csv
- Final analytic merge
  - FINAL_HAPI_ANALYTIC.csv
- ML model pipeline
  - RF + XGBoost + SHAP
- Fully reproducible end-to-end workflow
- Each domain debuggable independently

Data Flow Overview

End-to-end workflow from raw EHR inputs to a modeling-ready dataset.

Data Processing Pipeline & Feature Engineering Phases

HAPI Prediction Model Development

PHASE 1: LABELING

Build_HAPI_Labels

CSV

hospitalwide_hapi_labels.csv

PHASE 2: CORE FEATURES

Demographics → CSV demographics_feat.csv

Length of Stay → CSV los_feat.csv

Transfers → CSV icu_transfer.csv

I&O → CSV io_feat.csv

ICU Procedures → CSV icu_procedures_feat.csv

Notes (Discharge + Radiology) → CSV feat_notes.csv

PHASE 3: CODING & ORDERS

Diagnoses → CSV diagnoses_feat.csv

Procedures → CSV procedures_feat.csv

POE Orders → CSV poe_detail_feat.csv

PHASE 4: MEDICATIONS

Prescriptions → CSV prescriptions_feat.csv

MAR + MAR Detail → CSV emar_feat.csv

Pharmacy → CSV pharmacy_feat.csv

Merge Pharmacy Sources → CSV medications_master_feat.csv

PHASE 5: FINAL MERGE

master_merge_analytic

Fl

Modeling & Evaluation Pipeline

- Input: FINAL_HAPI_ANALYTIC.csv
- Train/Test Split: 80/20 (stratified by HAPI_FINAL)
- Models Evaluated:
  - Random Forest → baseline
  - XGBoost → advanced model

- Evaluation Metrics:
  - Accuracy, Precision, Recall, F1
  - ROC–AUC
  - Confusion matrices
- Explainability:
  - SHAP summary plots
  - Top predictive features
- Clinical Output:
  - Risk buckets: HIGH / MEDIUM / LOW
  - High-risk patient list for early prevention

Model Selection

Random Forest (Baseline):

- Handles nonlinear interactions, works well with many mixed clinical features, resistant to noise.

XGBoost:

- Gradient-boosted trees with strong performance on structured EHR data; good at capturing complex interactions.

Why These Models?

- Work well with tabular EHR data
- Handle missingness, nonlinearity, and feature interactions
- Fast to train and tune
- Widely used in clinical prediction research

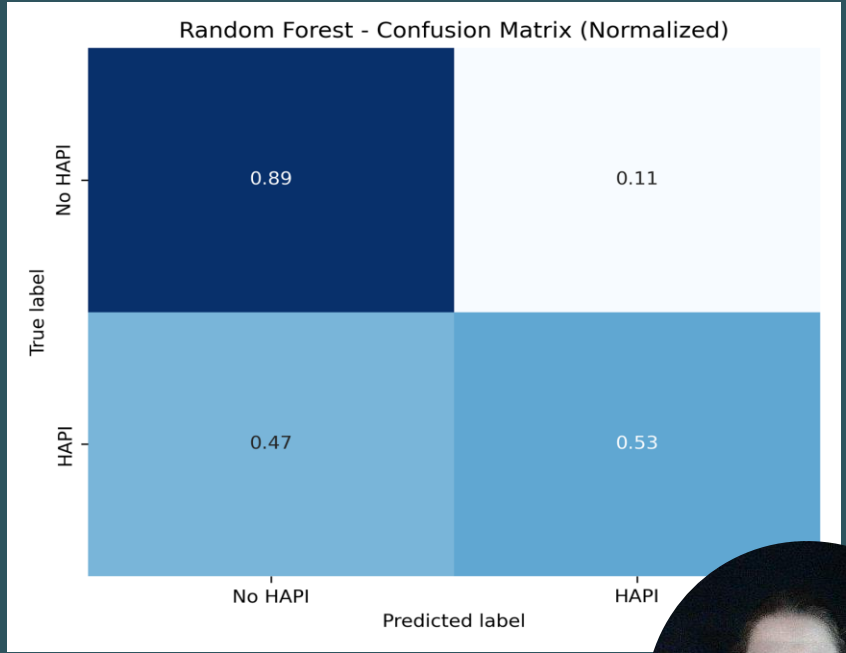
Model Results: Random Forest

Performance

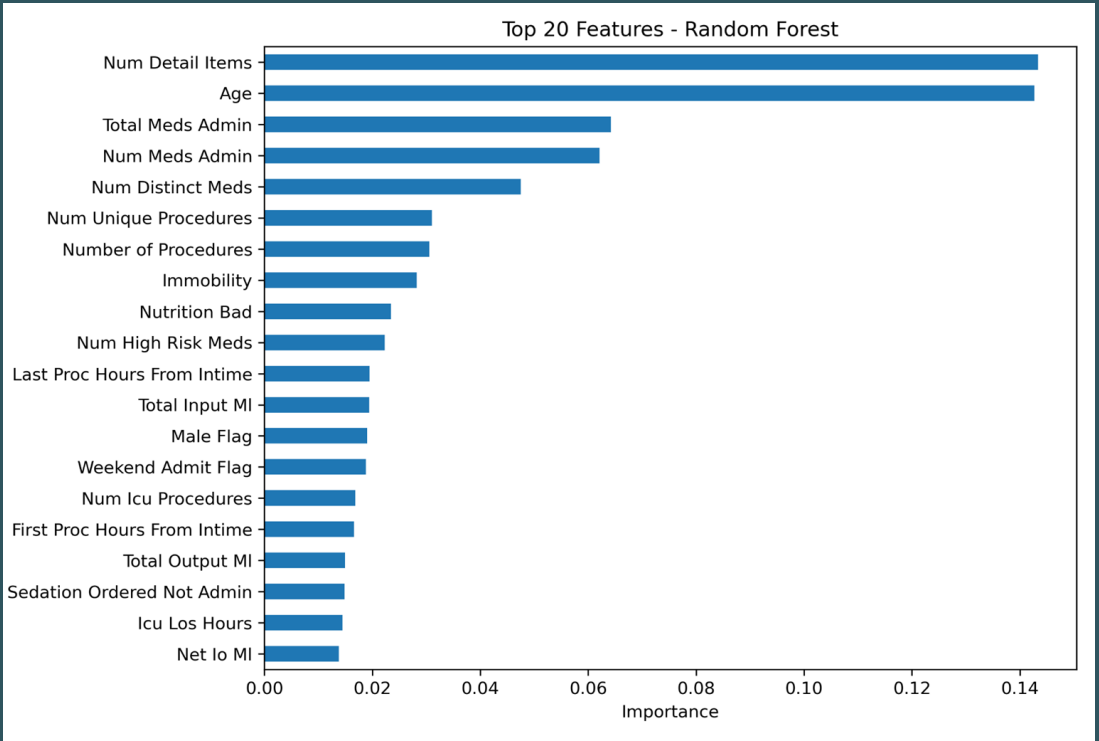
- No-HAPI correctly identified: 89%
- HAPI correctly identified (Recall): 53%
- More sensitive to true HAPI events

Key Predictors

- Medication complexity
- Procedure counts
- Immobility
- Nutrition risk
- ICU timing features



Model Results: Random Forest



Random Forest:

- Accuracy: 0.80
- HAPI Recall (Sensitivity): 0.53
- Precision (HAPI): 0.62
- F1 (HAPI): 0.57

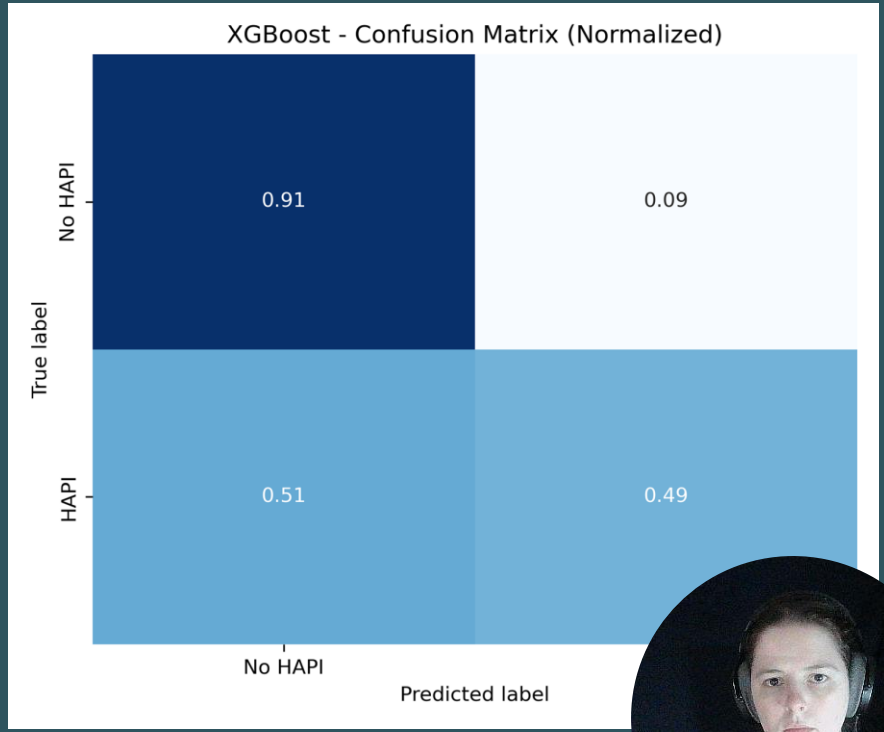
Model Results: XGBoost

Performance

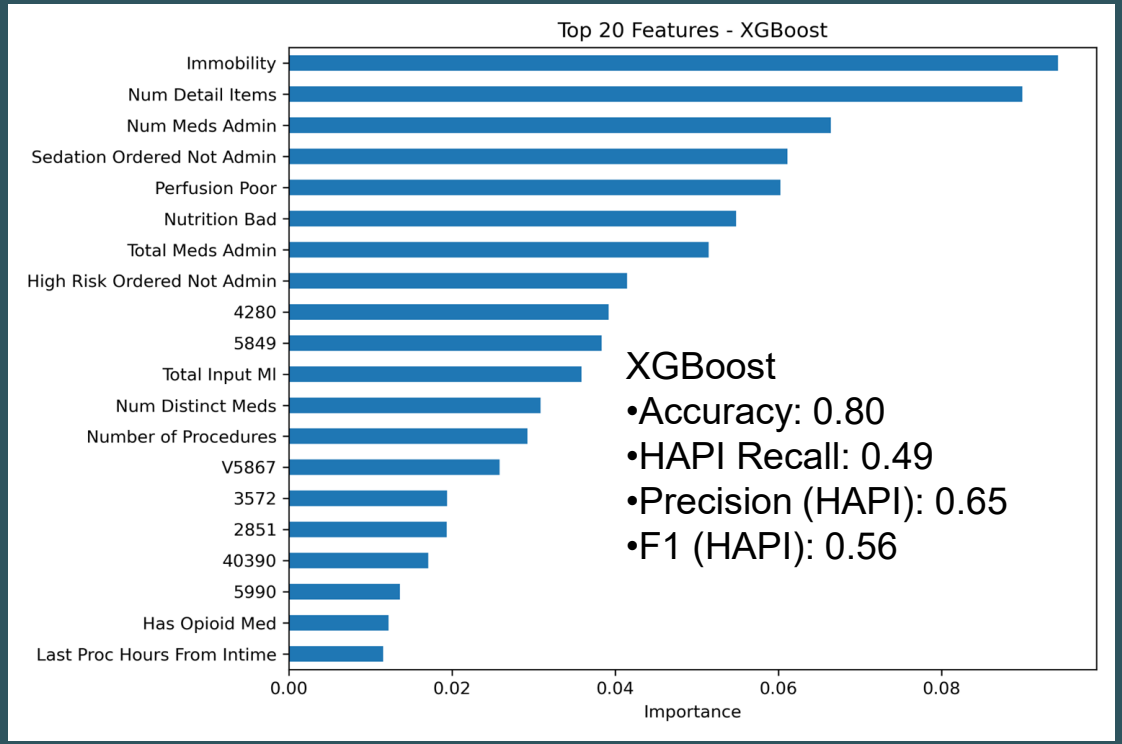
- No-HAPI correctly identified: 91%
- HAPI correctly identified (Recall): 49%
- More specific → fewer false positives
- Slightly more conservative than RF

Key Predictors

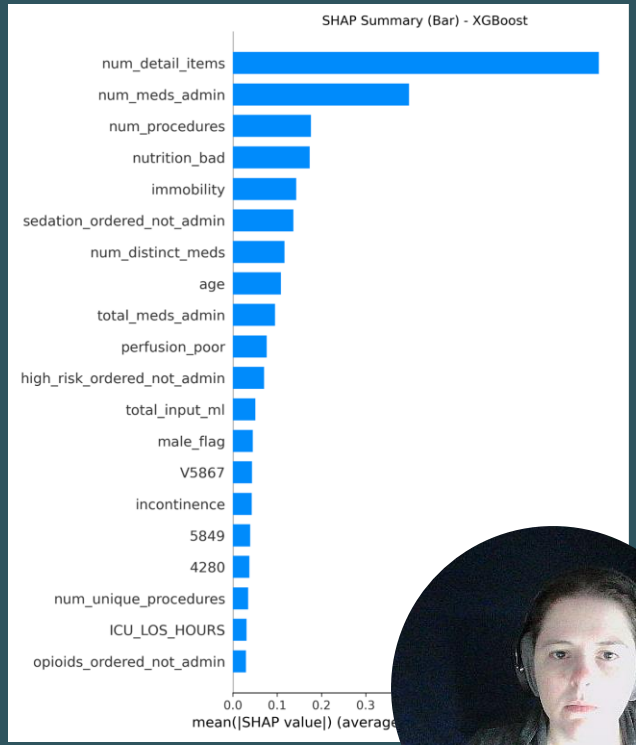
- Immobility
- Medication detail items
- Medication frequency
- Sedation ordered/not given
- Perfusion & nutrition status
- High-risk medications



Model Results: XGBoost



XGBoost
- Accuracy: 0.80
- HAPI Recall: 0.49
- Precision (HAPI): 0.65
- F1 (HAPI): 0.56



Conclusion

- Machine learning can enhance early identification of HAPI risk beyond traditional tools like the Braden Scale
- The models showed strong performance on No-HAPI cases and moderate sensitivity for true HAPI events
- Key predictors (immobility, nutrition, perfusion, medication complexity) match real clinical risk factors
- The pipeline is modular, reproducible, and scalable for future datasets
- Results support the potential for ML-driven decision support to guide earlier, personalized interventions

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Andrea Wroblewski
ahwroble@mtu.edu
https://github.com/AHWroblewski4/Data-Driven-Prediction-and-Prevention-of-Pressure