AI's Potential Role and Challenges in Critical Care and Chronic Disease Management

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Team Members

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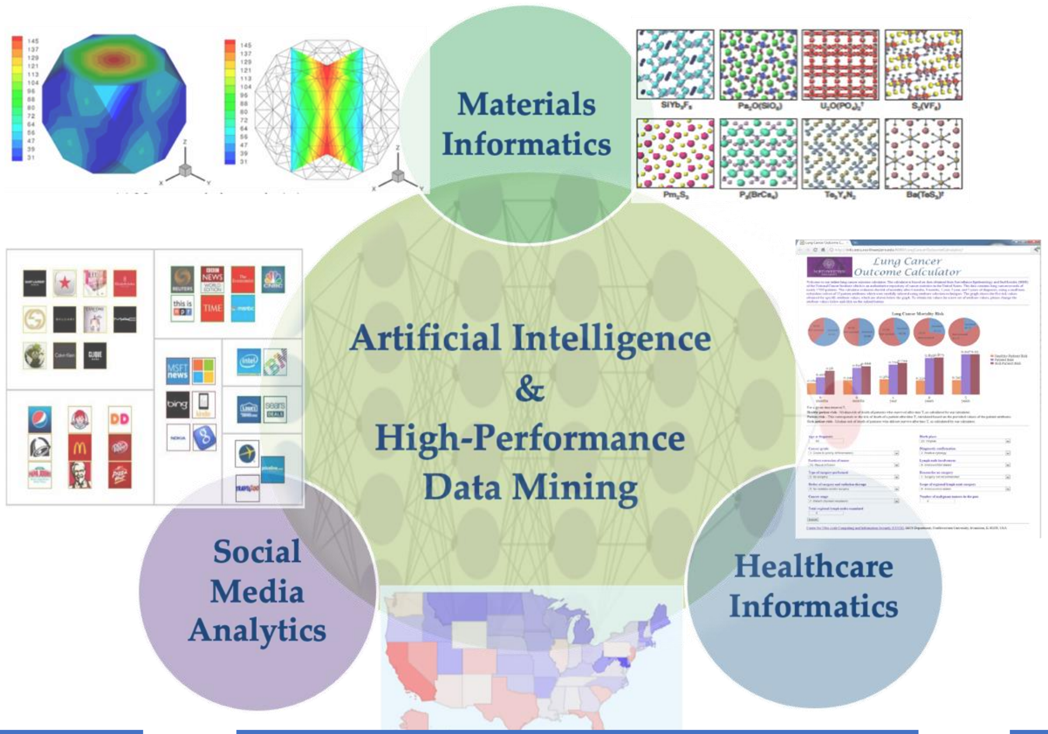
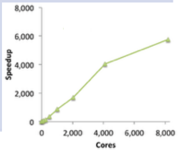
ECE and CS: **Alec Peltekian (PhD student)**, Prof. Ankit Agrawal, Prof. Alok Choudhary.

Our Research : Past 25+ years:



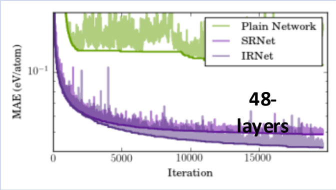
High Performance Computing (HPC)

- Parallel algorithm design, scalable AI/ML training
- Scientific Data management
- Parallel I/O



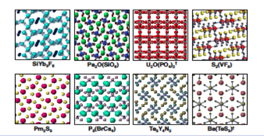
AI + Data Mining

- AI/ML algorithm design
- Deep learning
- Text mining
- Graph mining



Interdisciplinary Applications

- Materials science
- Healthcare + Life-sciences
- Social media
- Climate
- Etc.



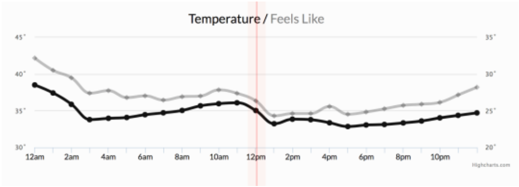
Artificial Intelligence for Science

A Deep Learning Revolution

editors

Alok Choudhary, Geoffrey Fox & Tony Hey

Typical AI Data vs Healthcare Data



Dense vs **Sparse**

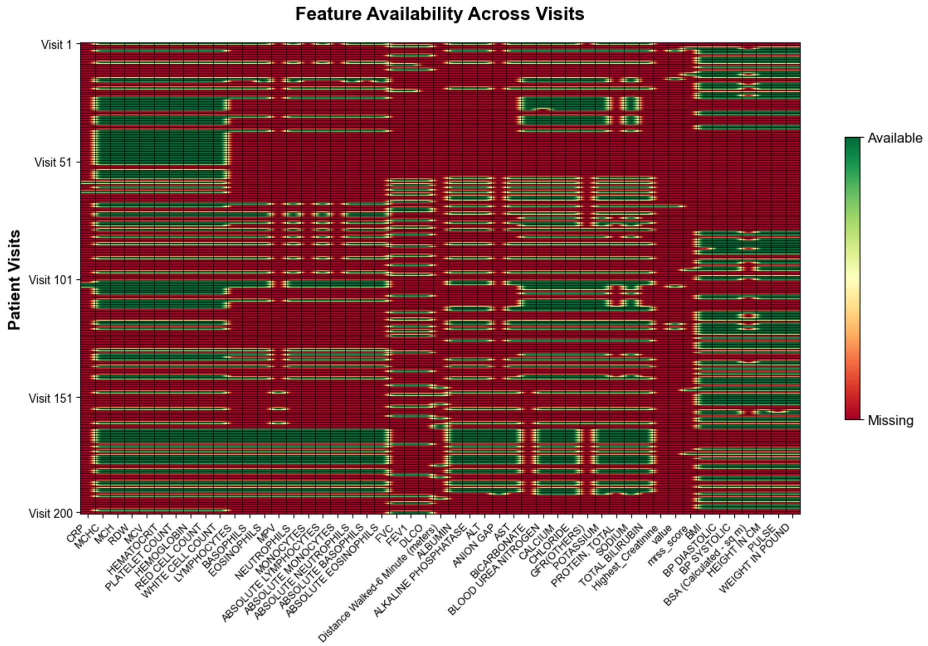
Every feature filled — Many missing values

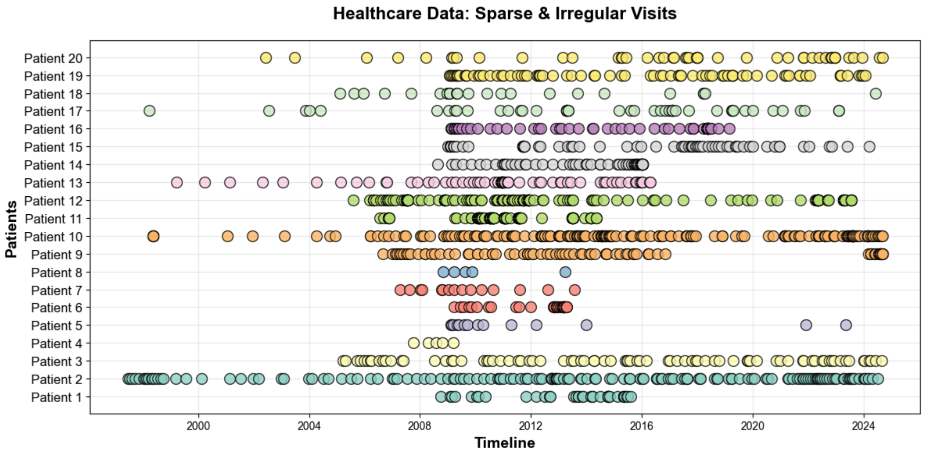
Complete vs **Missing**

Full Datasets — Incomplete Records

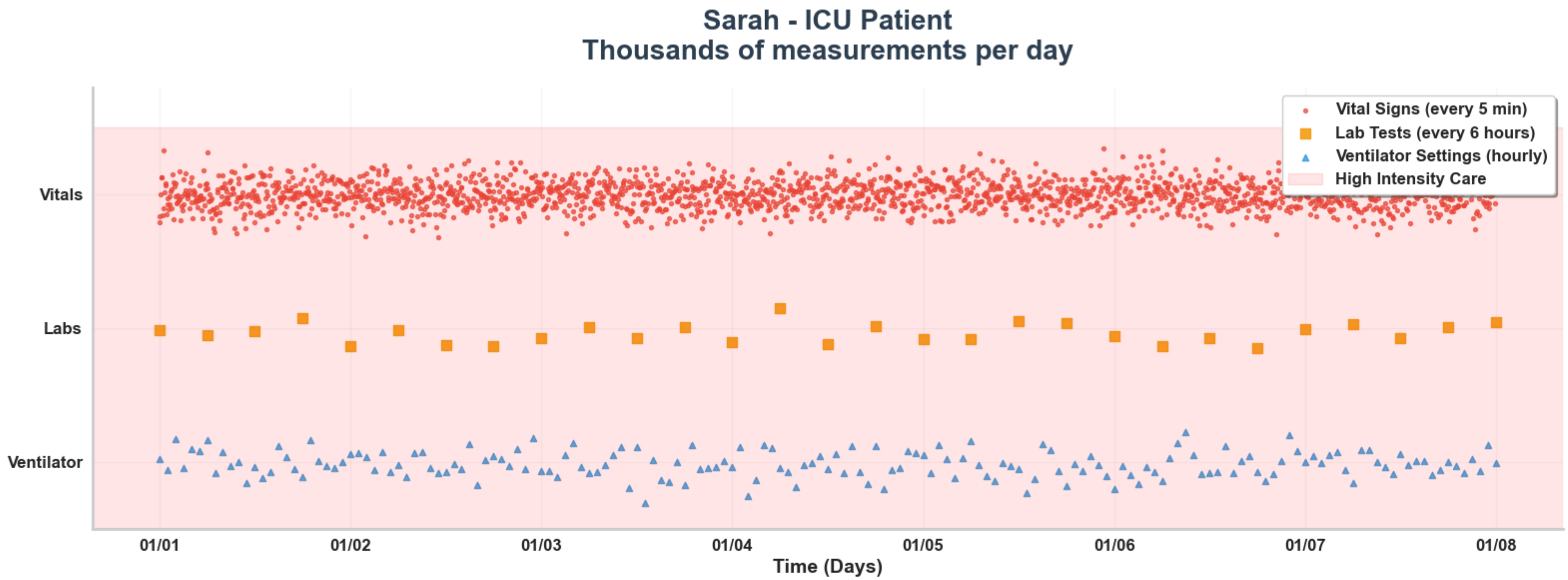
Regular vs **Irregular**

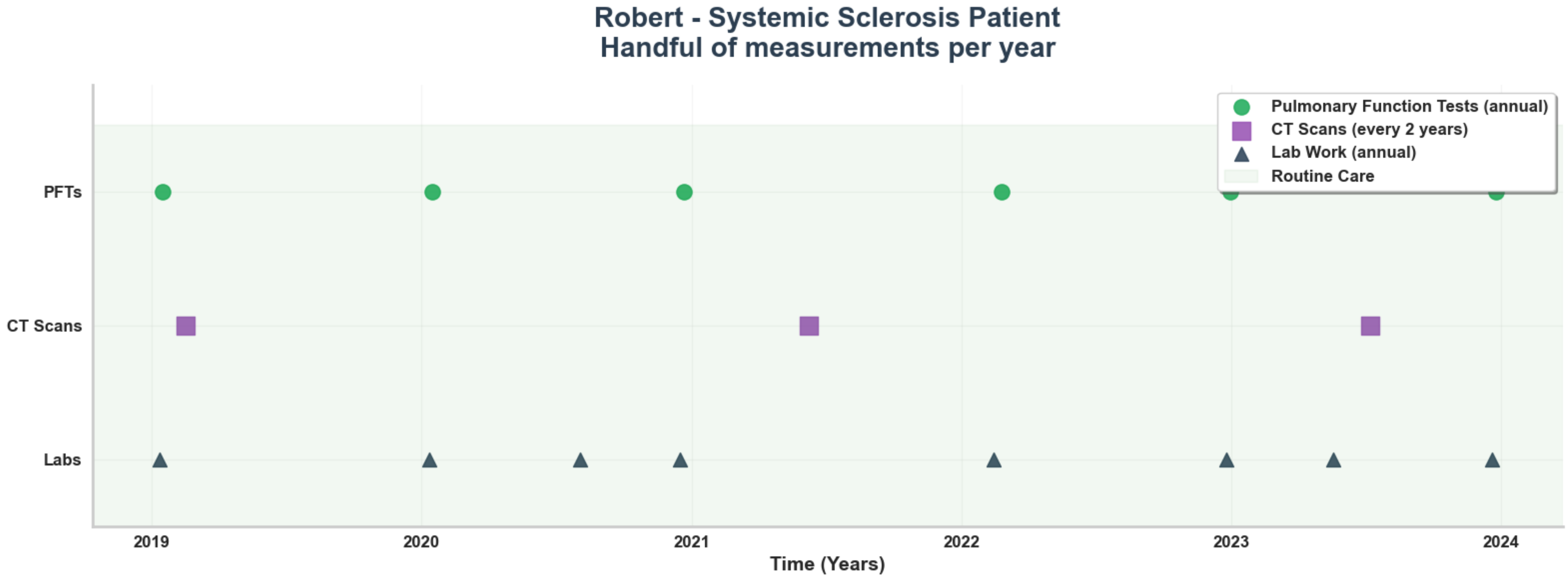
Consistent Timing — Variable Schedules



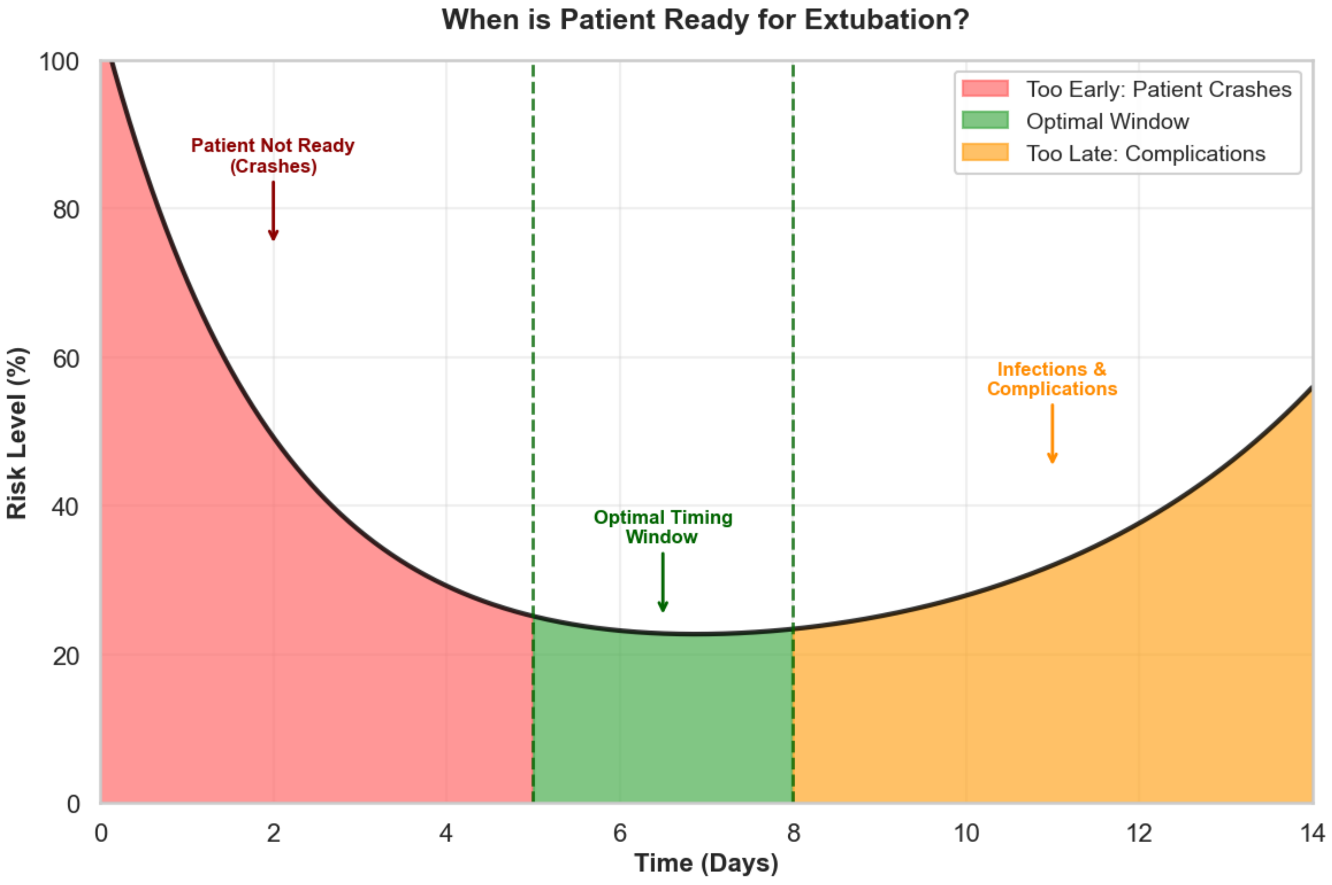


Meet Patients





The Clinical Stakes



Inpatient cases : Illustrative (related) questions for Doctor's decision – Today/Now

- Should the patient be extubated today? Tomorrow?
- Will patient develop VAP (Ventilator Associated Pneumonia)?
- Mortality?

AI-Enabled Clinical Decision Making

Doctors limited by:

- Processing thousands of datapoints
- Spotting subtle patterns over time time
- Subjective assessment variability

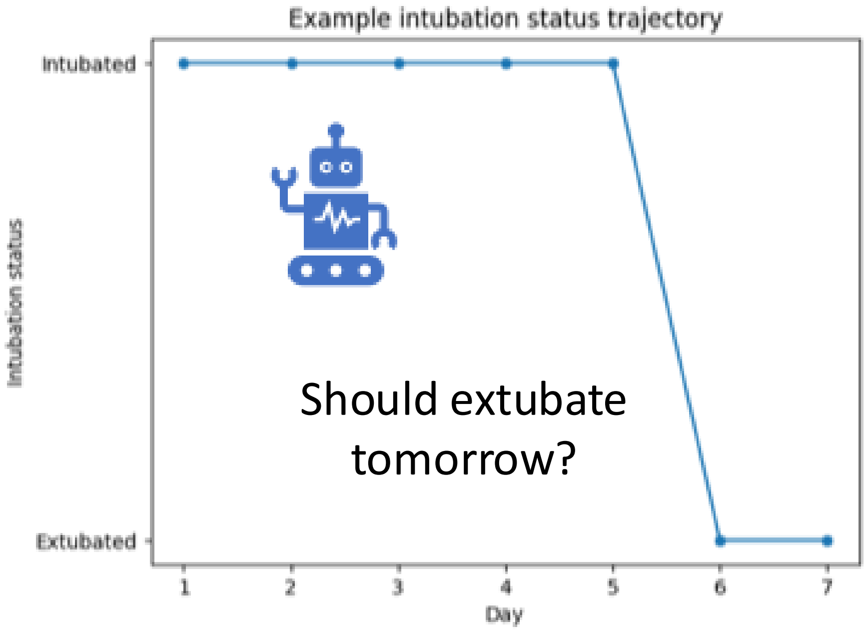
AI excels at:

- Analyzing datasets
- Detecting complex patterns
- Consistent objective analysis
- Unbiased signal detection

Goal: Complement human expertise, not replace it

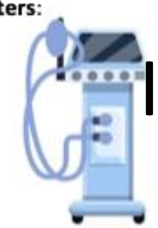
Problem Statement

"How to develop machine learning frameworks that handle complex, multimodal medical data across clinical clinical contexts - from dense ICU monitoring to sparse specialty care - - while leveraging sequential patterns patterns and patient cohorts for robust robust predictive performance and clinical interpretability."



Mental status: GCS (eye opening, motor response, verbal response), RASS

Ventilator parameters:
PEEP
Plateau pressure
Compliance
Changes
ECMO



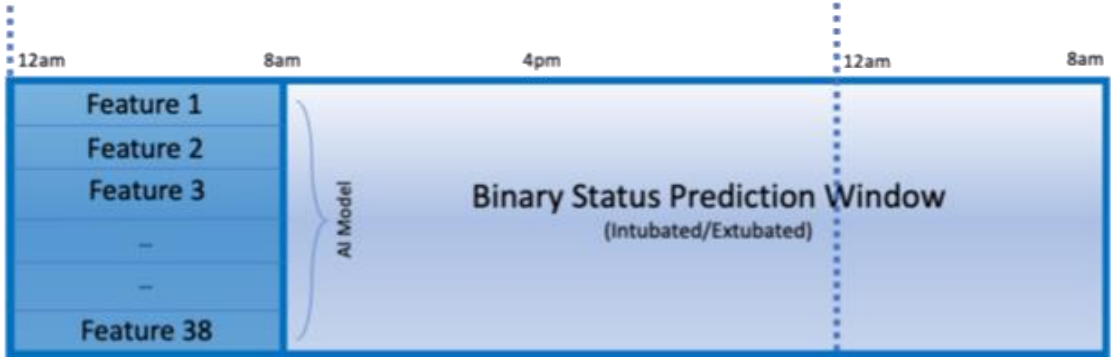
ICU dataset

Vitals
Vasopressors

690 patients
15,203 days

Laboratory values:
Leukocytes
Lymphocytes
Neutrophils
Procalcitonin
Hemoglobin
Lactate
Ferritin
Bicarbonate
Albumin
Bilirubin
Platelets

Dialysis
CRRT
Urine output



Extubation Prediction

When to Attempt Successful Extubation in the in the ICU

Too Early:

- Crash
- Failed extubations (Put patient back on < 48 hours) hours)

Too Late:

- Ventilator-associated pneumonia
- Prolonged Stay (Bed usage)

Current Approach: Subjective doctor assessment + breathing trials

Rich ICU Monitoring Data (From the SCRIPT study)

Dataset

448 patients, 3,095 ICU patient-days

External validation: 333 patients

Method

37 clinical features (midnight to 8AM) to predict next-day day extubation readiness readiness

Timing

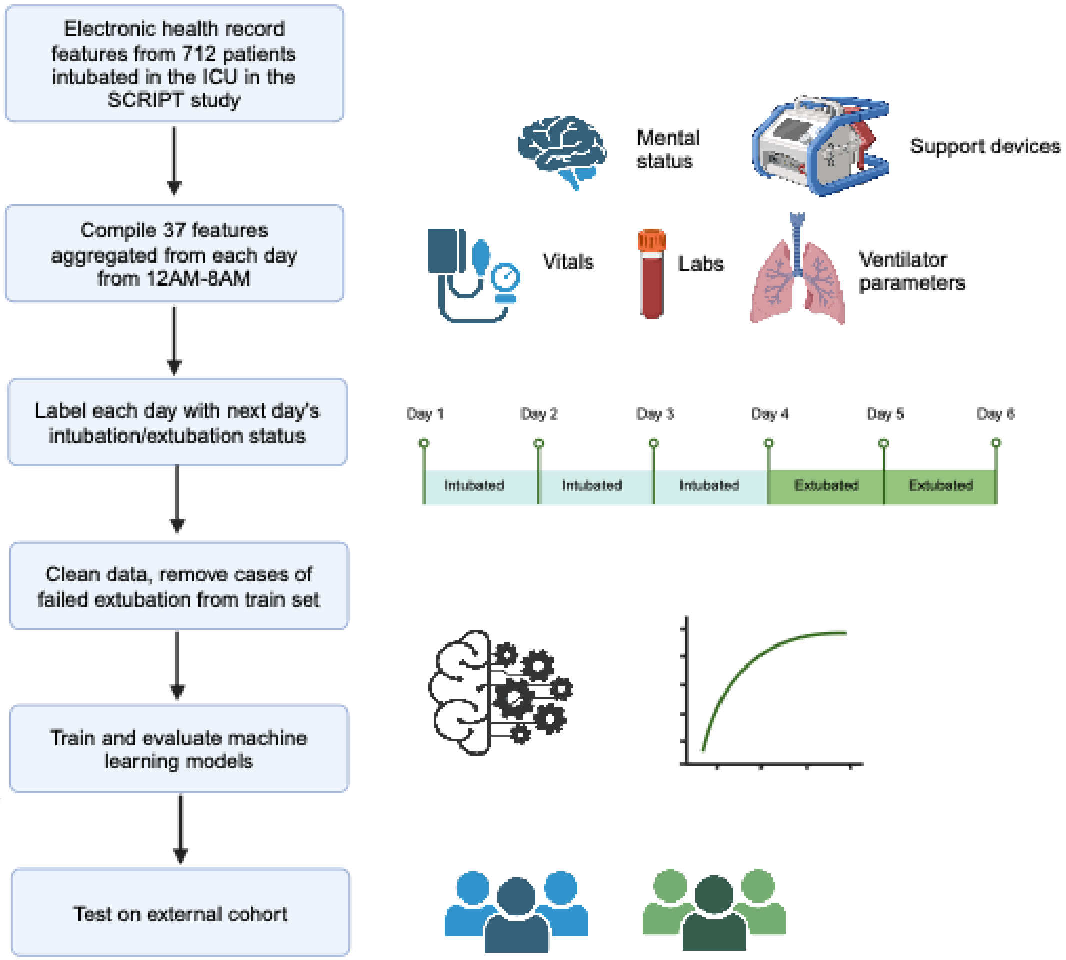
Aligned with morning rounds for actionable insights

Article | Open access | Published: 29 July 2025

Developing and validating machine learning models to predict next-day extubation

Samuel W. Fenske, Alec Peltekian, Mengjia Kang, Nikolay S. Markov, Mengou Zhu, Kevin Grudzinski, Melissa J. Bak, Anna Pawlowski, Vishu Gupta, Yuwei Mao, Stanislav Bratchikov, Thomas Stoeger, Luke V. Rasmussen, Alok N. Choudhary, Alexander V. Misharin, Benjamin D. Singer, G. R. Scott Budinger, Richard G. Wunderink, Ankit Agrawal, Catherine A. Gao & NU SCRIPT Study Investigators

Scientific Reports **15**, Article number: 27552 (2025) | Cite this article



Nature Scientific Reports

Learning From Missing Data

Missing ≠ Random

Missing often means "patient stable" – Traditional approaches to dealing with missing data DON'T work. Missing data itself could be a signal!

Preserve missing data information

Explicitly encode when data is missing as a meaningful signal

Create meaningful ranges

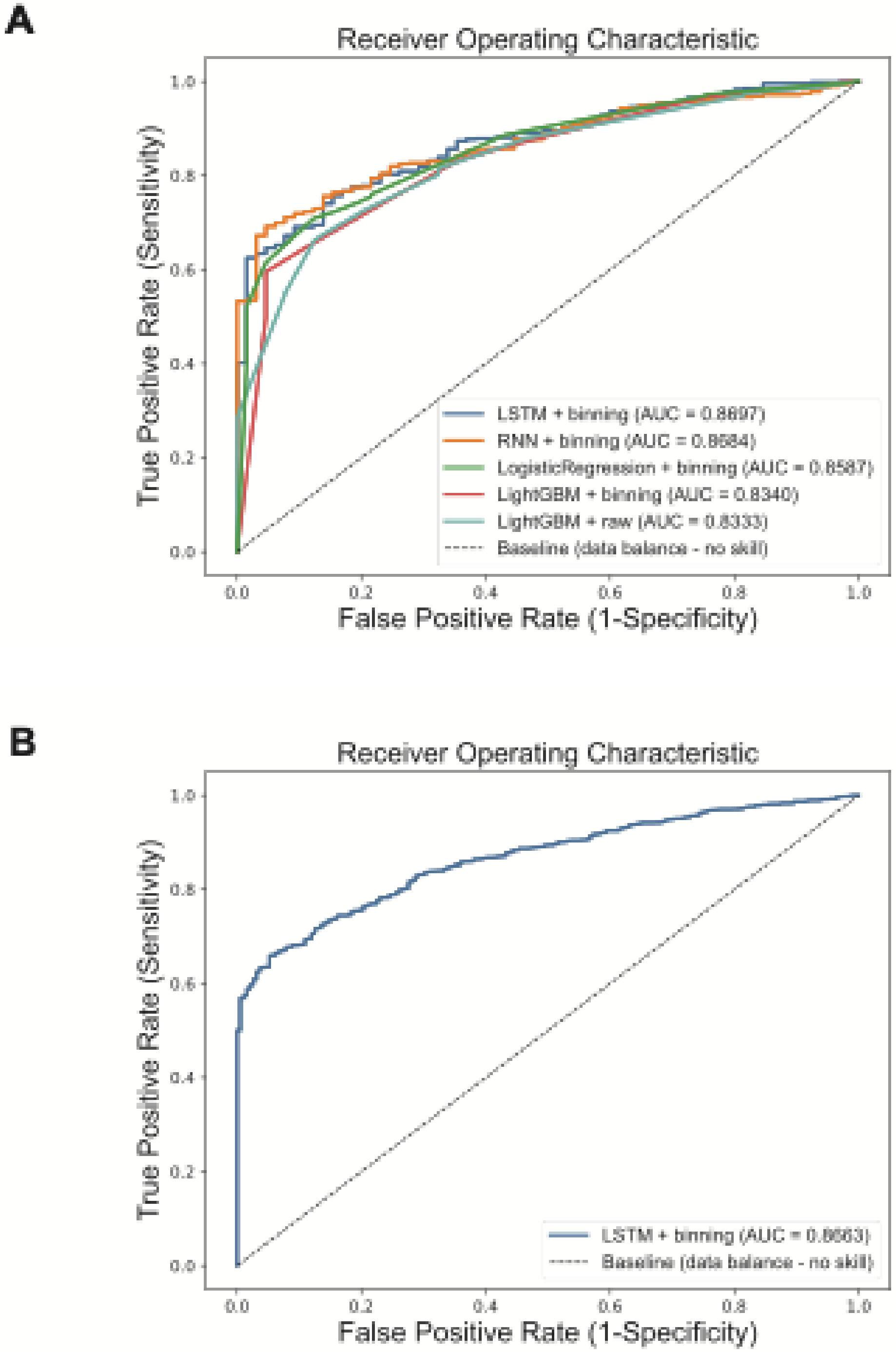
Divide continuous variables into clinically relevant relevant categories

Keep clinical significance

Maintain interpretability for healthcare professionals professionals

Day	Temperature_mask (Missing)	Temperature [-∞, 98.03) (0-25%)	Temperature [98.03, 98.59) (25-50%)	Temperature [98.59, 99.35) (50-75%)	Temperature [99.35, ∞] (75-100%)
1	0	0	0	0	1
2	0	0	0	1	0
3	0	0	1	0	0
4	1	0	0	0	0
5	0	1	0	0	0

Strong Results Across Hospitals



LSTM 0.870 AUC

Validation Success:

- ✓ Internal Cohort
- ✓ External Validation

Models Agree with Clinicians (experience) – Critical for Trust + Explainability

Key Features:

Mental Status

Glasgow Coma Scale, RASS score

Lung Function

Plateau pressure, PEEP settings

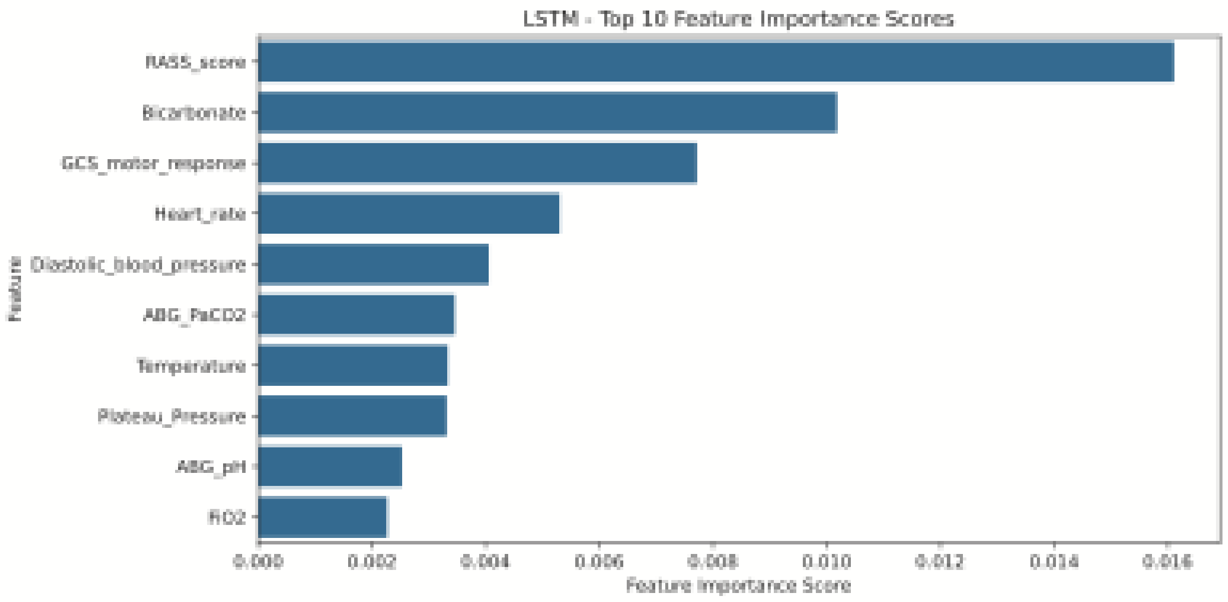
Overall Stability

Heart rate, blood pressure

Respiratory Support

Oxygen needs

- ✓ Matches medical criteria
- ✓ Clinically interpretable
- ✓ Doctors can trust the reasoning



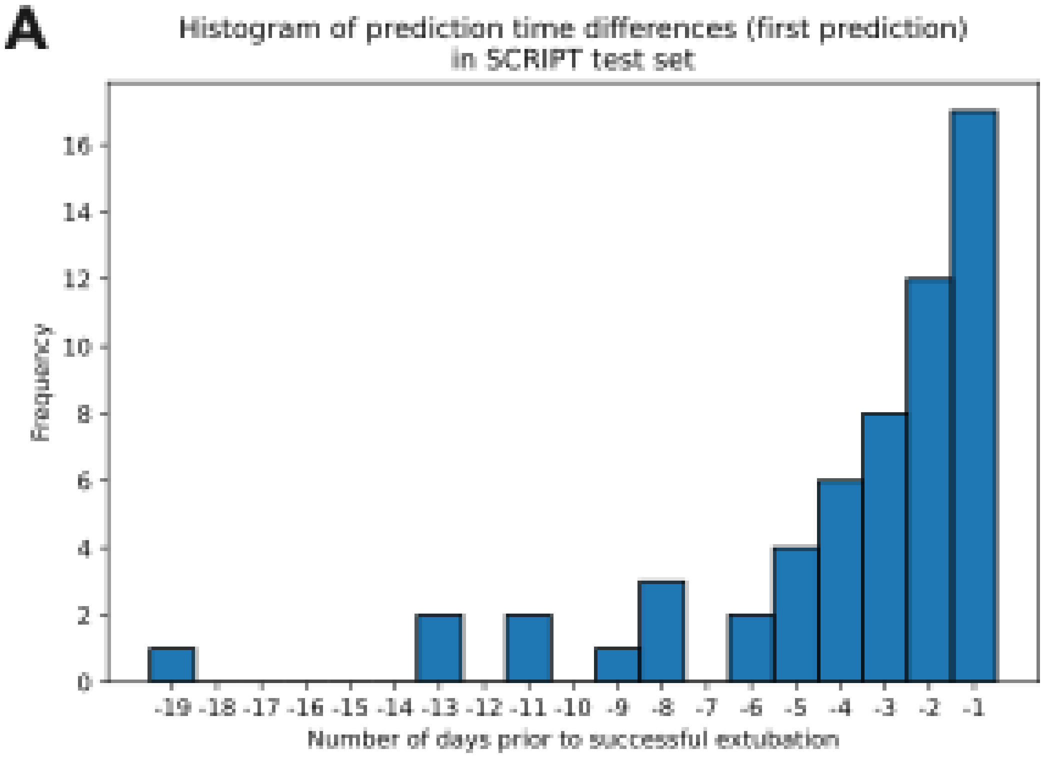
Models Predict Earlier Readiness

models often identified readiness days days before doctors acted

Potential for earlier, safer liberation on 58 attempts (934 intubation days - **93.8% correct**)

63.8% (37) of "incorrect” (58) predictions within 3 days of actual event

Models flagged 35.4% of failed extubations (17/48)

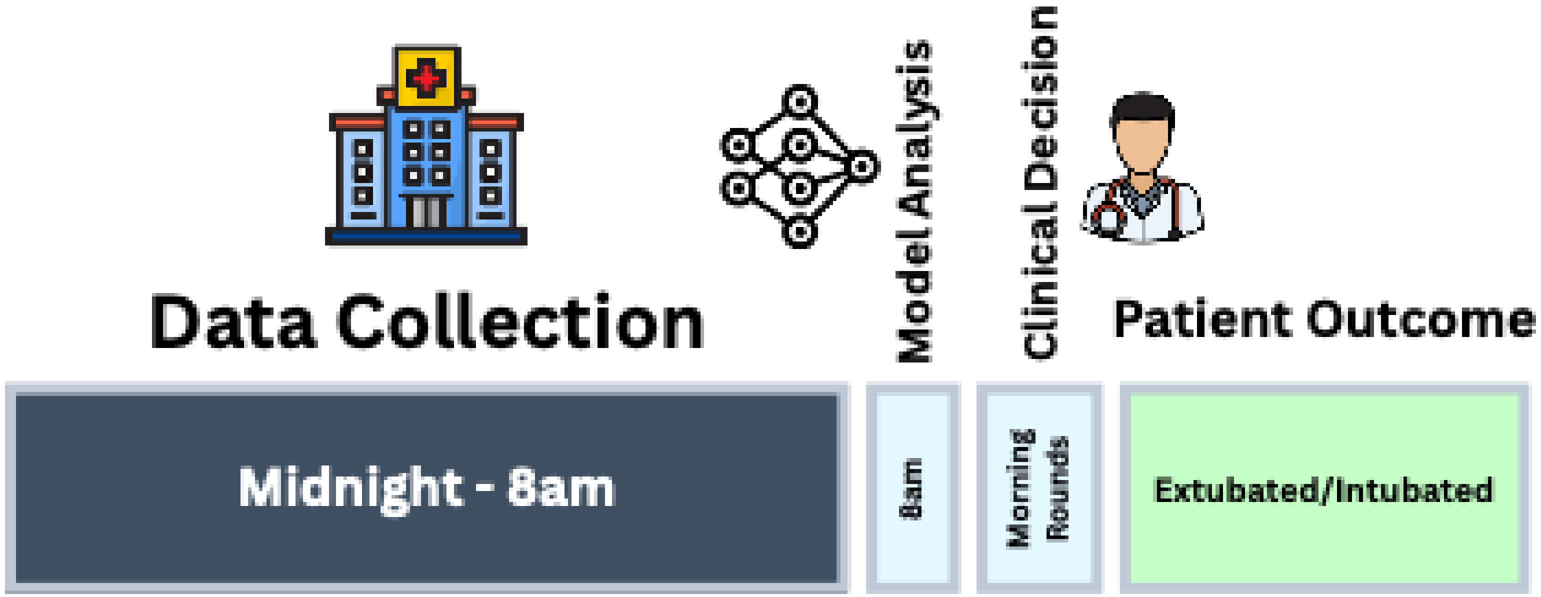


Result: Shorter ICU stays, fewer complications complications

Clinical Translational Approach

Designed for In-Hospital Use:

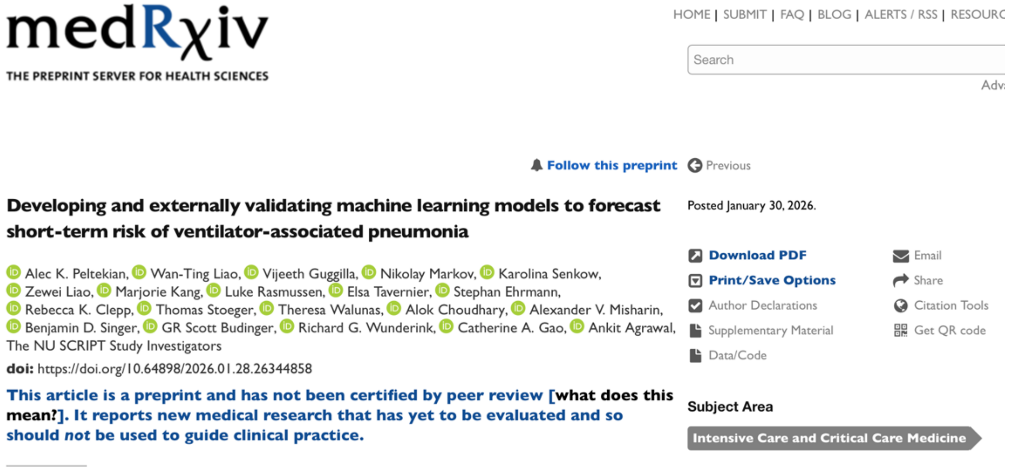
- Uses only data available by 8AM
- Decision support, not replacement



Workflow:

Overnight analysis → Risk score → Enhanced clinical decisions

VAP Prediction



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Developing and externally validating machine learning models to forecast short-term risk of ventilator-associated pneumonia

Alec K. Peltekian, Wan-Ting Liao, Vijeeth Guggilla, Nikolay Markov, Karolina Senkow, Zewei Liao, Marjorie Kang, Luke Rasmussen, Elsa Tavernier, Stephan Ehrmann, Rebecca K. Clepp, Thomas Stoeger, Theresa Walunas, Alok Choudhary, Alexander V. Misharin, Benjamin D. Singer, GR Scott Budinger, Richard G. Wunderink, Catherine A. Gao, Ankit Agrawal, The NU SCRIPT Study Investigators

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This article is a preprint and has not been certified by peer review [what does this mean?]. It reports new medical research that has yet to be evaluated and so should *not* be used to guide clinical practice.

Posted January 30, 2026.

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Subject Area

Intensive Care and Critical Care Medicine

Same ICU decision point – different risk to anticipate

Extubation: Are they ready to come of the ventilator tomorrow?

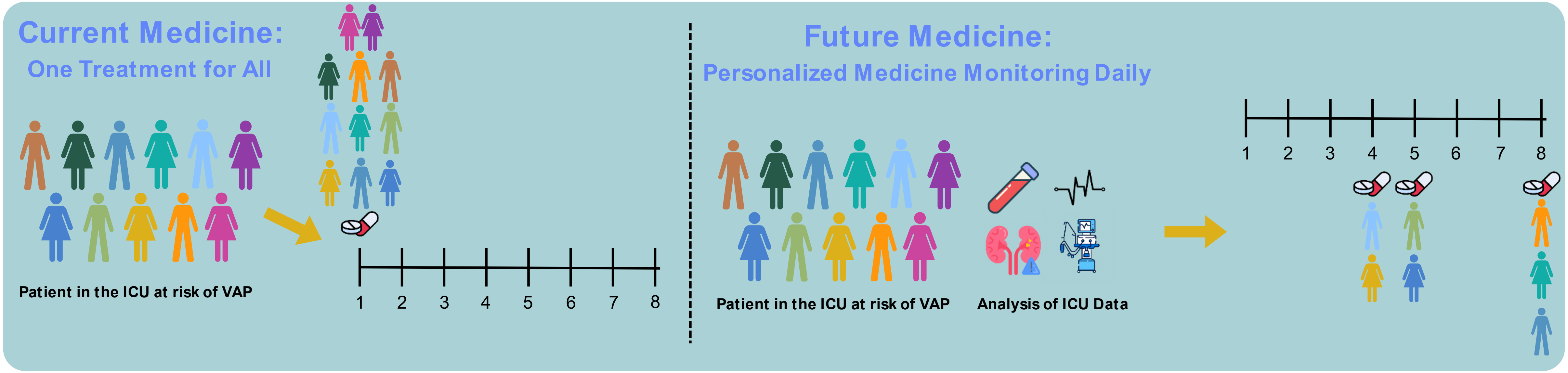
VAP: Are they at risk of infection if we keep them on?

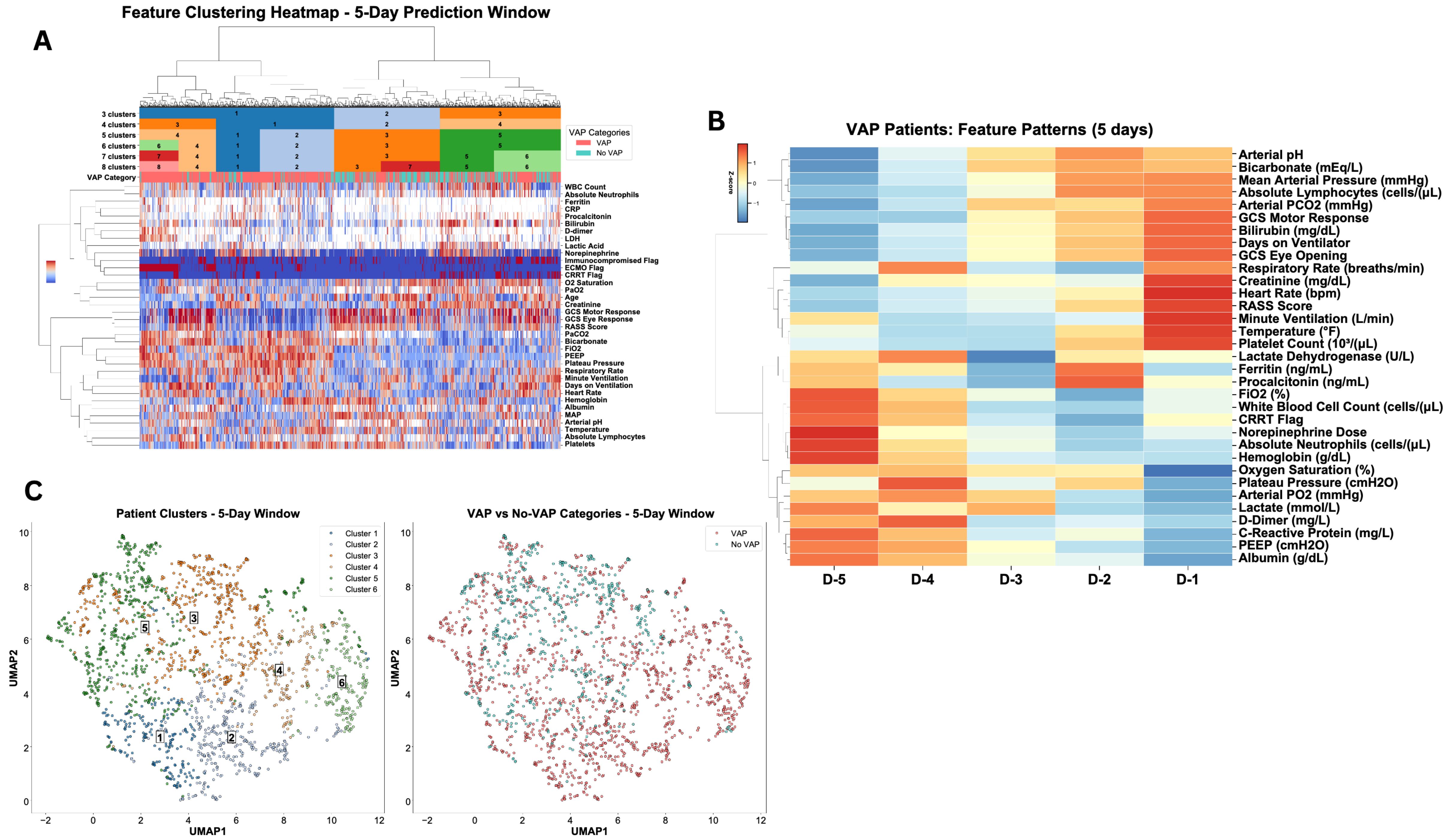
Clinical Need:

VAP affects 10-20% of ventilated patients
- Need for personalized care

The Challenge:

Predict infection risk while patients
patients remain ventilated

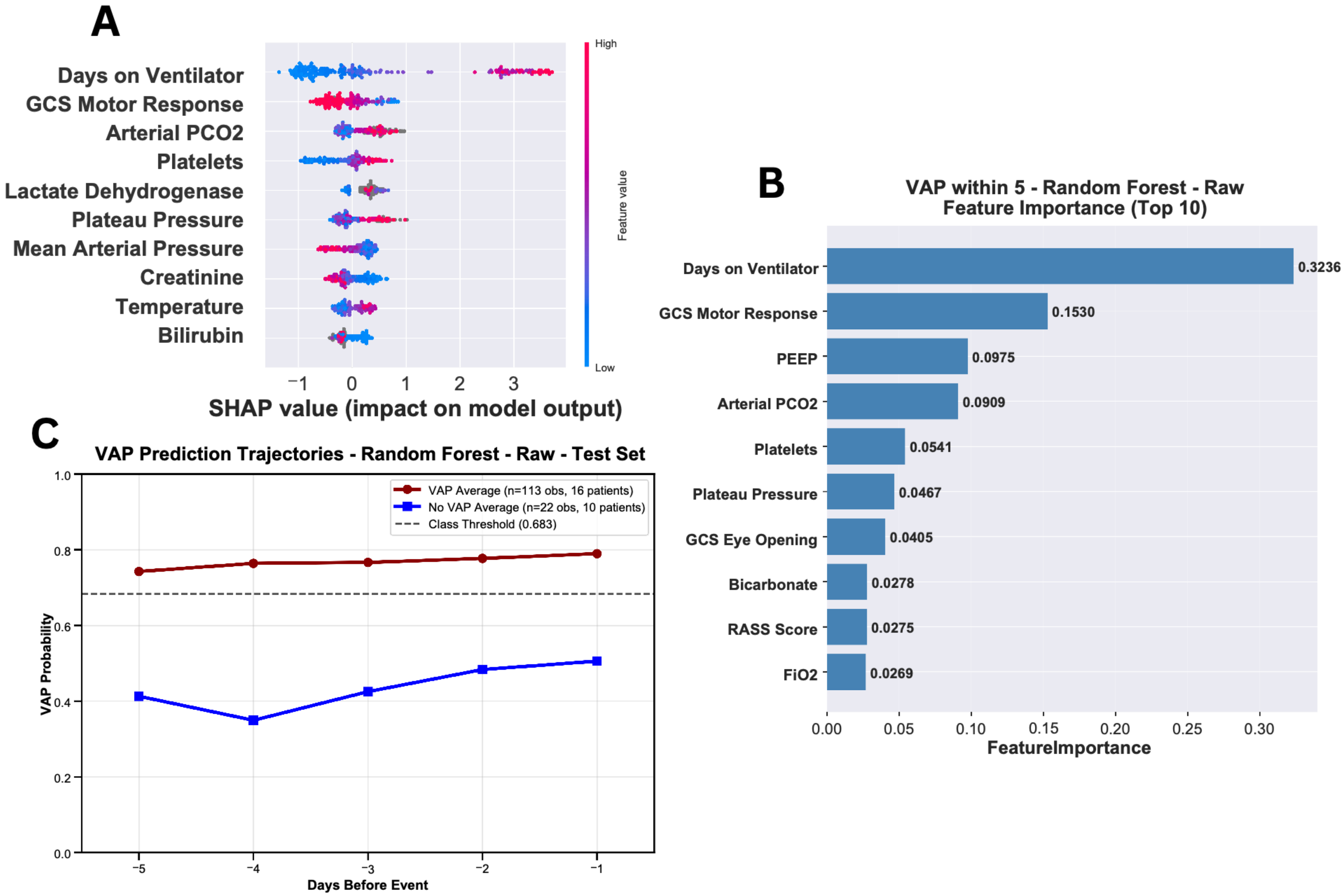




Feature Clustering Heatmap - 5-Day Prediction Window
A
3 clusters
4 clusters
5 clusters
6 clusters
7 clusters
8 clusters
VAP Category
VAP Categories
VAP
No VAP
WBC Count
Absolute Neutrophils
Ferritin
CRP
Procalcitonin
Bilirubin
D-dimer
LDH
Lactic Acid
Norepinephrine
Immunocompromised Flag
ECMO Flag
CRRT Flag
O2 Saturation
PaO2
Age
Creatinine
GCS Motor Response
GCS Eye Response
RASS Score
PaCO2
Bicarbonate
FiO2
PEEP
Plateau Pressure
Respiratory Rate
Minute Ventilation
Days on Ventilation
Heart Rate
Hemoglobin
Albumin
MAP
Arterial pH
Temperature
Absolute Lymphocytes
Platelets
B
VAP Patients: Feature Patterns (5 days)
Z-score
Arterial pH
Bicarbonate (mEq/L)
Mean Arterial Pressure (mmHg)
Absolute Lymphocytes (cells/(μL)
Arterial PCO2 (mmHg)
GCS Motor Response
Bilirubin (mg/dL)
Days on Ventilator
GCS Eye Opening
Respiratory Rate (breaths/min)
Creatinine (mg/dL)
Heart Rate (bpm)
RASS Score
Minute Ventilation (L/min)
Temperature (°F)
Platelet Count (10³/(μL)
Lactate Dehydrogenase (U/L)
Ferritin (ng/mL)
Procalcitonin (ng/mL)
FiO2 (%)
White Blood Cell Count (cells/(μL)
CRRT Flag
Norepinephrine Dose
Absolute Neutrophils (cells/(μL)
Hemoglobin (g/dL)
Oxygen Saturation (%)
Plateau Pressure (cmH2O)
Arterial PO2 (mmHg)
Lactate (mmol/L)
D-Dimer (mg/L)
C-Reactive Protein (mg/L)
PEEP (cmH2O)
Albumin (g/dL)
D-5
D-4
D-3
D-2
D-1
C
Patient Clusters - 5-Day Window
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6
UMAP1
UMAP2
VAP vs No-VAP Categories - 5-Day Window
VAP
No VAP
UMAP1
UMAP2

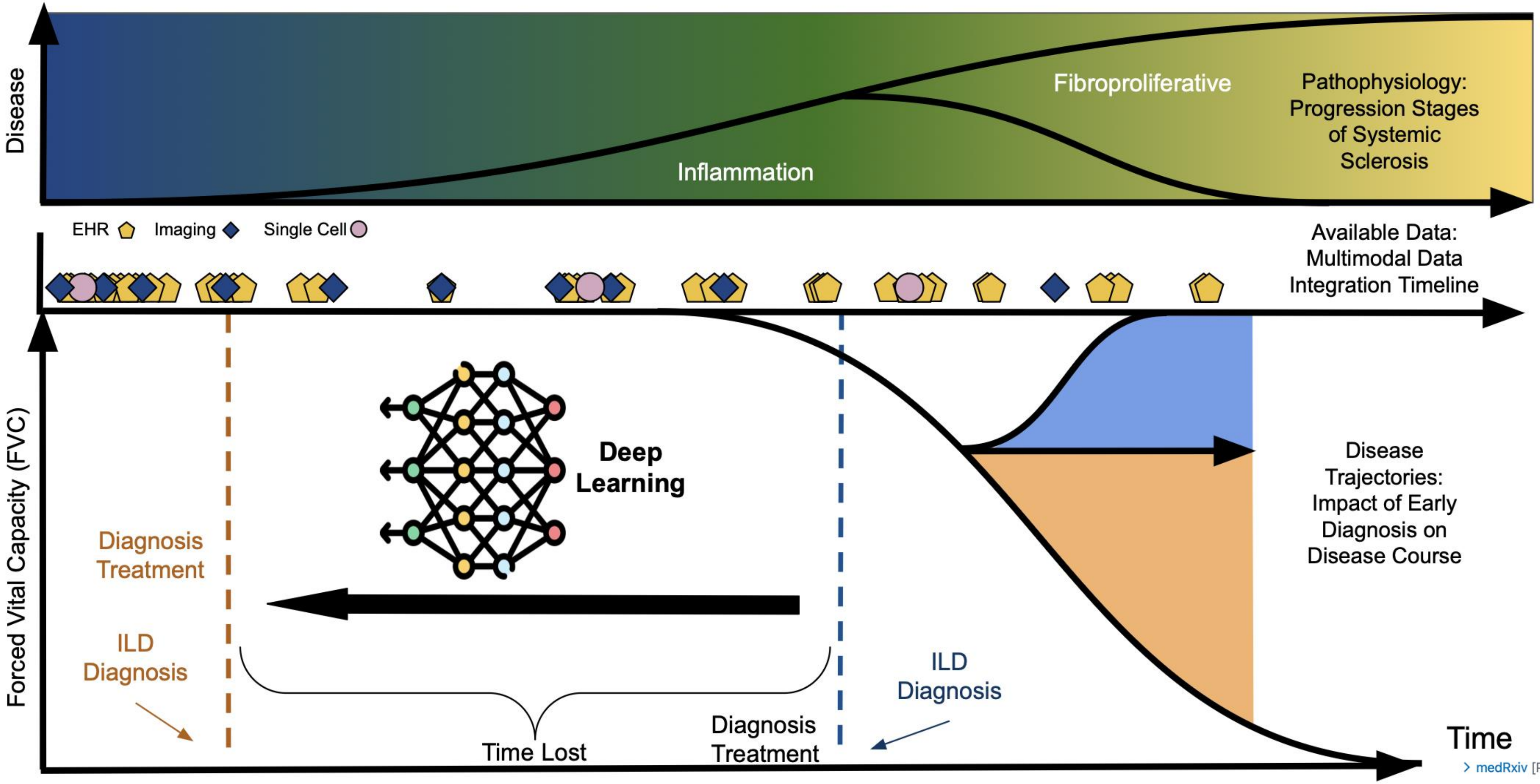
SCRIPT cohort results:

Task Model	AUC	AUPRC	Accuracy	F1
VAP Within 3 Days				
XGBoost (raw)	0.721 (0.626–0.797)	0.878 (0.819–0.921)	0.625 (0.539–0.703)	0.711 (0.622–0.779)
Random Forest (raw)	**0.806 (0.732–0.874)**	**0.918 (0.876–0.952)**	**0.750 (0.672–0.820)**	**0.828 (0.766–0.881)**
XGBoost (binned)	0.756 (0.670–0.830)	0.899 (0.849–0.937)	0.656 (0.578–0.734)	0.711 (0.619–0.784)
Random Forest (binned)	0.769 (0.682–0.844)	0.902 (0.854–0.941)	0.695 (0.609–0.773)	0.775 (0.699–0.835)
Logistic Regression (binned)	0.725 (0.637–0.809)	0.881 (0.826–0.927)	0.664 (0.578–0.742)	0.749 (0.671–0.815)
LSTM (binned)	0.765 (0.676–0.850)	0.899 (0.844–0.943)	0.617 (0.531–0.703)	0.642 (0.543–0.731)
VAP Within 5 Days				
XGBoost (raw)	0.706 (0.634–0.772)	0.871 (0.826–0.911)	0.613 (0.543–0.678)	0.680 (0.612–0.744)
Random Forest (raw)	**0.843 (0.782–0.894)**	**0.931 (0.896–0.959)**	**0.789 (0.729–0.844)**	**0.842 (0.789–0.887)**
XGBoost (binned)	0.747 (0.677–0.807)	0.891 (0.851–0.926)	0.658 (0.588–0.719)	0.728 (0.661–0.787)
Random Forest (binned)	0.780 (0.715–0.838)	0.905 (0.866–0.938)	0.729 (0.663–0.784)	0.799 (0.740–0.846)
Logistic Regression (binned)	0.716 (0.643–0.781)	0.869 (0.823–0.911)	0.653 (0.588–0.714)	0.732 (0.669–0.786)
LSTM (binned)	0.840 (0.782–0.892)	0.928 (0.893–0.957)	0.774 (0.714–0.829)	0.812 (0.756–0.861)
VAP Within 7 Days				
XGBoost (raw)	0.812 (0.757–0.863)	0.904 (0.867–0.933)	0.745 (0.687–0.795)	0.766 (0.703–0.818)
Random Forest (raw)	0.846 (0.799–0.889)	**0.916 (0.880–0.943)**	0.764 (0.714–0.811)	**0.817 (0.769–0.858)**
XGBoost (binned)	0.816 (0.760–0.866)	0.906 (0.869–0.936)	0.761 (0.707–0.811)	0.780 (0.720–0.829)
Random Forest (binned)	0.826 (0.773–0.876)	0.910 (0.874–0.938)	0.737 (0.680–0.788)	0.793 (0.738–0.839)
Logistic Regression (binned)	0.792 (0.735–0.843)	0.890 (0.850–0.923)	0.687 (0.629–0.741)	0.746 (0.690–0.798)
LSTM (binned)	**0.866 (0.820–0.909)**	0.904 (0.846–0.948)	**0.772 (0.722–0.822)**	0.803 (0.747–0.852)



A
Days on Ventilator
GCS Motor Response
Arterial PCO2
Platelets
Lactate Dehydrogenase
Plateau Pressure
Mean Arterial Pressure
Creatinine
Temperature
Bilirubin
−1 0 1 2 3
SHAP value (impact on model output)
High
Feature value
Low
B
VAP within 5 - Random Forest - Raw
Feature Importance (Top 10)
Days on Ventilator 0.3236
GCS Motor Response 0.1530
PEEP 0.0975
Arterial PCO2 0.0909
Platelets 0.0541
Plateau Pressure 0.0467
GCS Eye Opening 0.0405
Bicarbonate 0.0278
RASS Score 0.0275
FiO2 0.0269
0.00 0.05 0.10 0.15 0.20 0.25 0.30
FeatureImportance
C
VAP Prediction Trajectories - Random Forest - Raw - Test Set
VAP Average (n=113 obs, 16 patients)
No VAP Average (n=22 obs, 10 patients)
Class Threshold (0.683)
VAP Probability
0.0 0.2 0.4 0.6 0.8 1.0
−5 −4 −3 −2 −1
Days Before Event

Using AI to Predict, Prevent, and Treat SSc-ILD



Sparse Longitudinal Modeling

> medRxiv [Preprint]. 2025 Jun 4:2025.06.02.25328786. doi: 10.1101/2025.06.02.25328786.

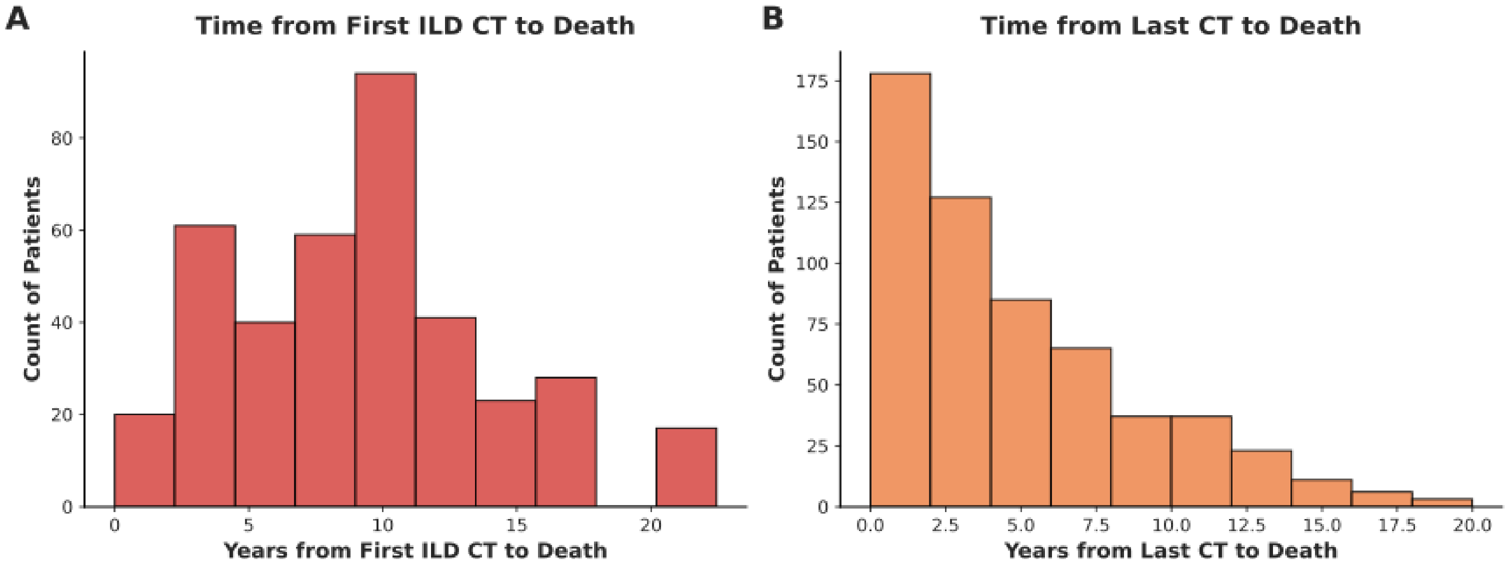
Machine Learning Analysis of Electronic Health Records Identifies Interstitial Lung Disease and Predicts Mortality in Patients with Systemic Sclerosis

Alec K Peltekian [1], Kevin M Grudzinski [2], Bradford C Bemiss [2,3], Jane E Dematte [2,3], Carrie Richardson [4], Nikolay S Markov [2,3], Mary Carns [2], Kathleen Aren [4], Natania S Field [4], Mengou Zhu [5], Alexandra Soriano [2], Matthew Dapas [4], Harris Perlman [4], Aaron Gundersheimer [2], Kavitha C Selvan [2,3], Duncan F Moore [4], Luke V Rasmussen [6], John Varga [7], Monique Hinchcliff [8,9], Krishnan Warrior [2,3], Catherine A Gao [2,3], Richard G Wunderink [2,3], Gr Scott Budinger [2,3], Alok Choudhary [1,10], Alexander V Misharin [2,3], Ankit Agrawal [3,10], Anthony J Esposito [2,3]

Affiliations + expand

PMID: 40502596 PMCID: PMC12155007 DOI: 10.1101/2025.06.02.25328786

Why SSc-ILD Imaging Matters



CT Scans Provide:

Direct disease visualization

See actual lung changes in detail

Regional progression patterns

Track how disease spreads through lungs

Subtle early changes

Detect disease before symptoms appear

The Gap: Labs normal, but CT shows scarring

Opportunity: AI finds hidden prognostic signals

Disease Variability – The Core Challenge

Same disease, Different outcomes

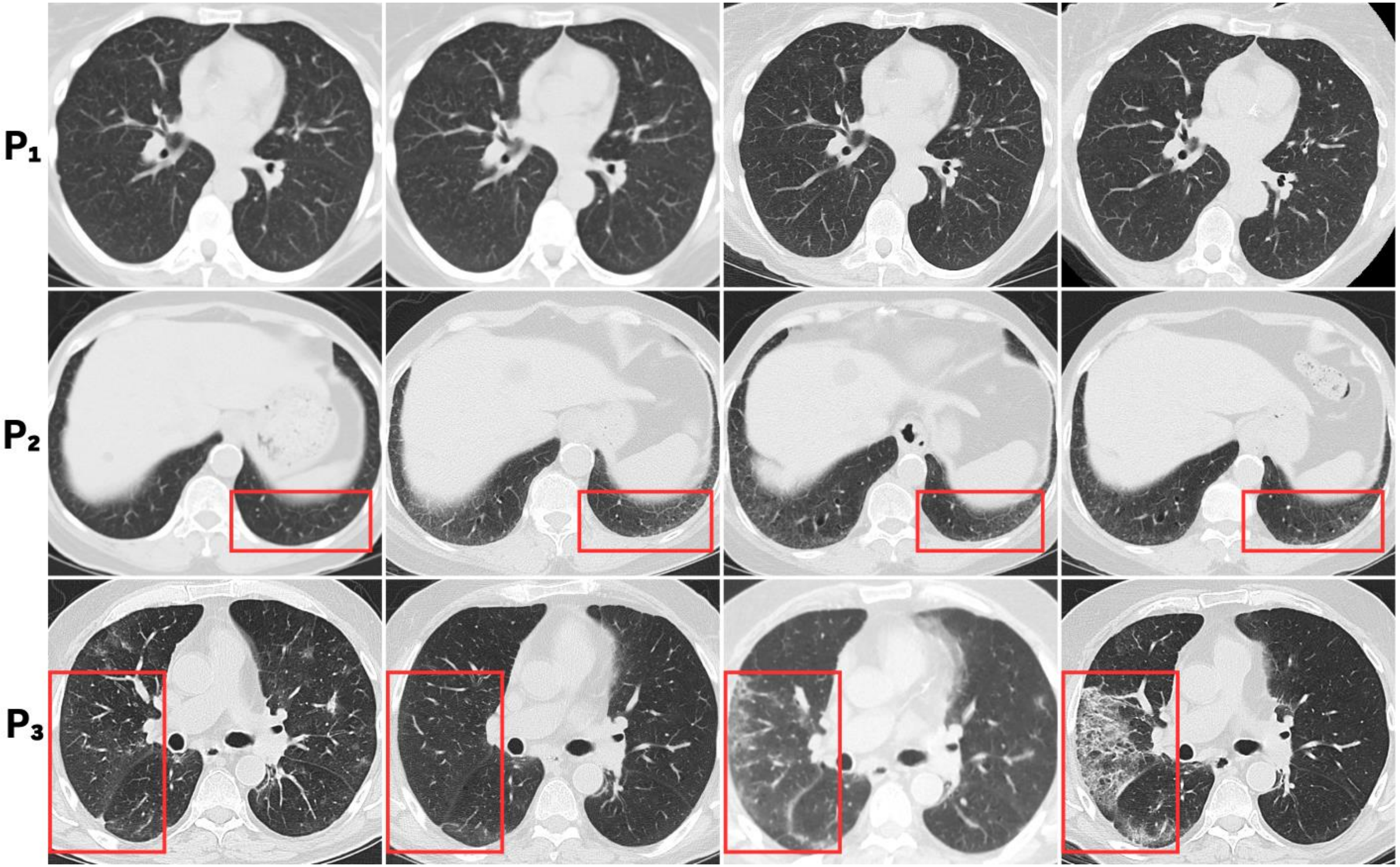
- Some live 10+ years
- Others die in 2-3 years
- Current tools can't predict outcomes

Three Patients Examples

P1
Stable scans over years

P2
Gradual progression over decade

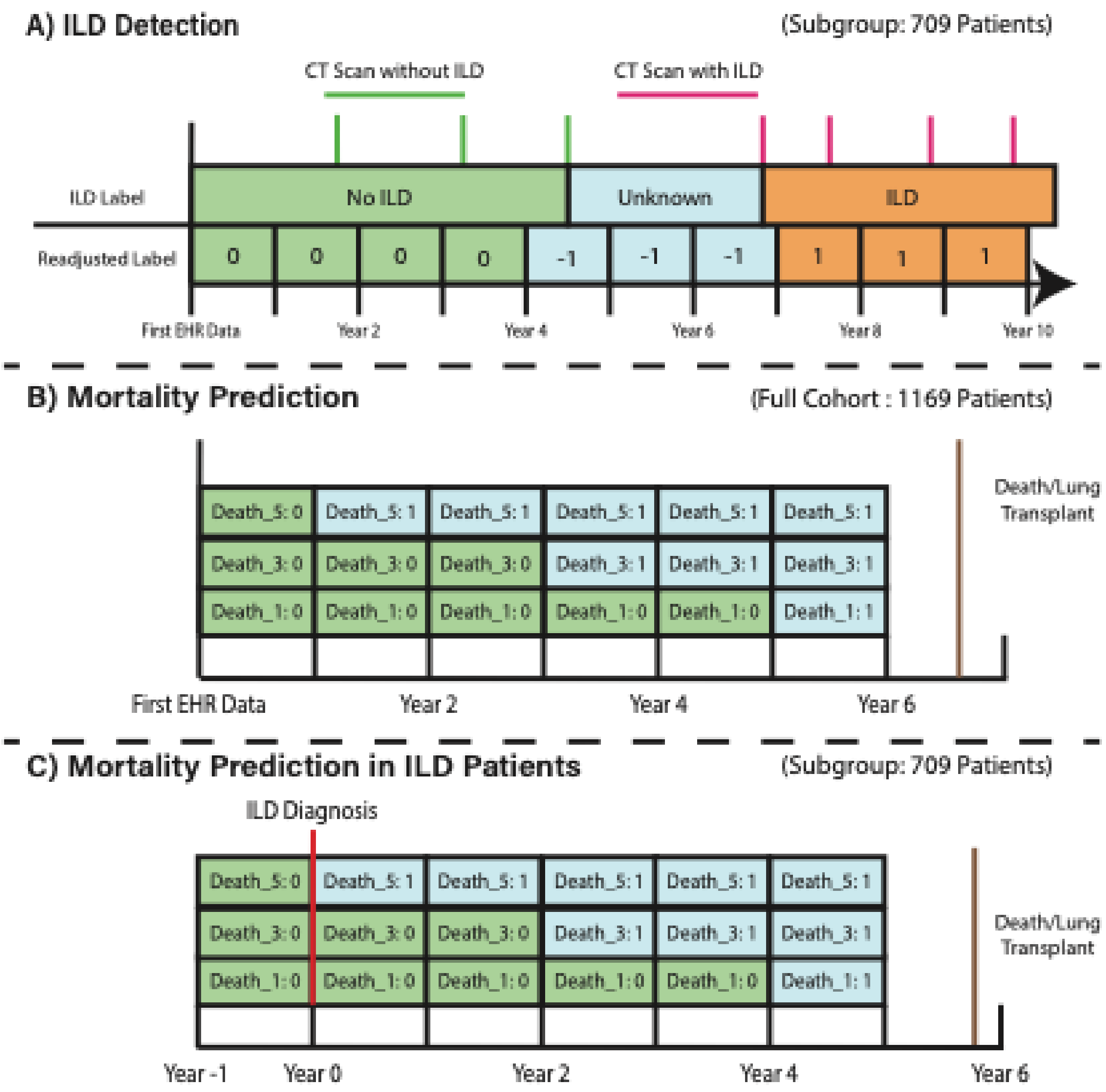
P3
Rapid deterioration in 3 years



Same Disease, Completely Different Trajectories Trajectories

Patients with the same diagnosis can follow dramatically different disease disease courses, making prediction particularly challenging.

> SSc-ILD patients exhibit highly variable disease progression patterns, with some remaining stable for for years while others deteriorate rapidly.



Three Major Prediction Tasks

1. ILD Detection

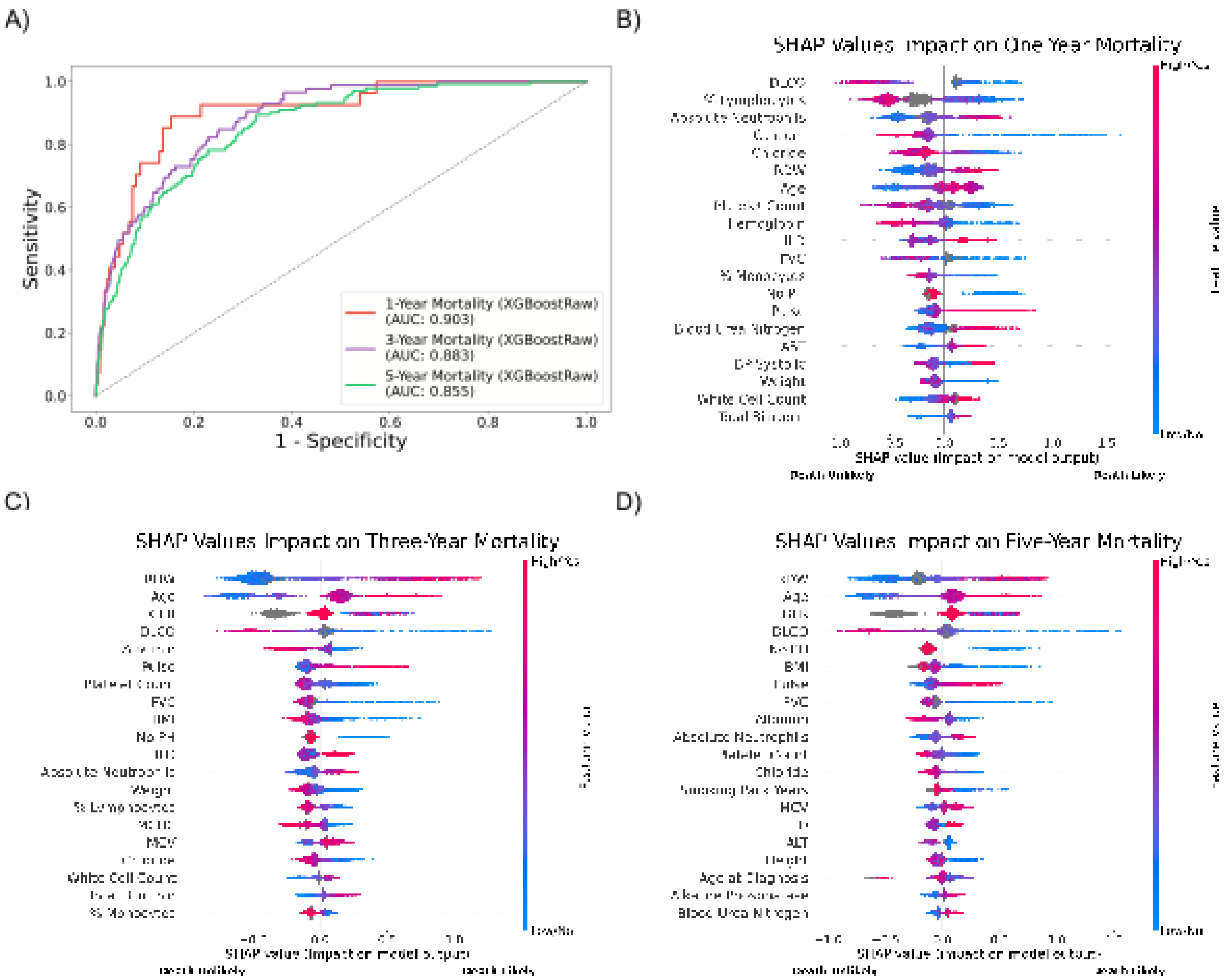
Earlier lung disease identification

2. Mortality (All)

1, 3, and 5 year survival prediction

3. Mortality (ILD)

Postdiagnosis survival guidance



Models Found Unexpected Biomarkers

Expected Predictors:

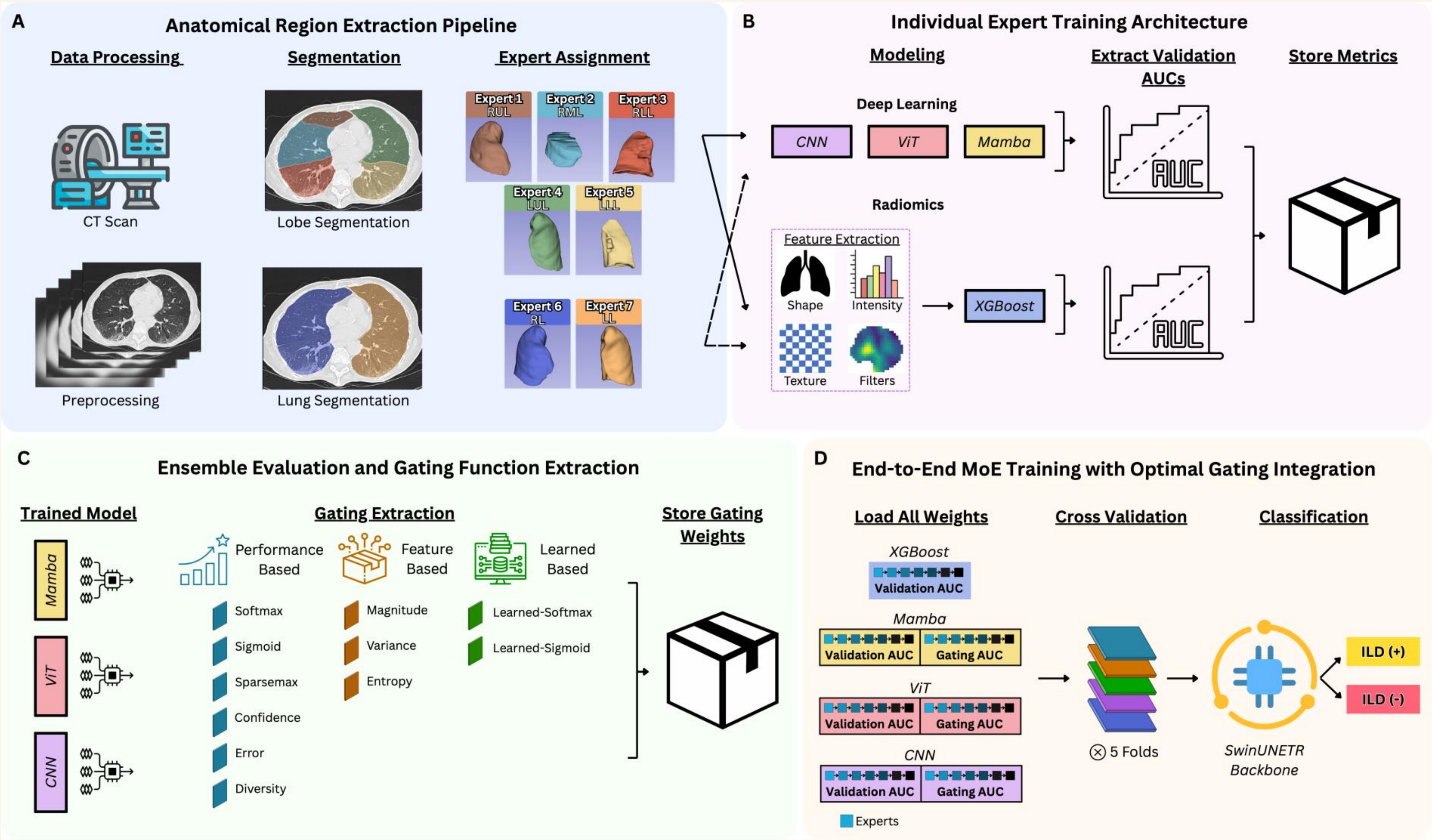
- Lung function tests (DLCO, FVC)
- Disease-specific antibodies
- Age and disease subtype

Surprising Discoveries:

- Red blood cell width (inflammation)
- Serum chloride (metabolic function)
- White blood cell patterns patterns (immune activity) activity)

Mixture of Experts

- **Regional Masking**
  Experts sees only their region
- **Smart Gating**
  Trust weighting
- **Specialized Training**
  Region-specific patterns
- **Combined Decision**
  All expert opinions



Expert Models:

CNN, Vision Transformer, Mamba

Radiomic Features:

Traditional radiology features (texture, shape, intensity)

Innovation:

Medical knowledge in AI architecture

Challenging Clinical Problems – addressed!

Extubation Prediction + VAP Onsent Prediction

SSc EHR modeling (mortality prediciton)

Imaging (CT) mortality prediction (direct disease signal)

Anatomical MoE (regional expert networks – Lung aware modeling)

Multimodal MoE (EHR+CT integration) – Patient Specific Reasoning

AI's Potential Role and Challenges in Critical Care and Chronic Disease Management

THANK YOU!

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