Korea Clinical Datathon 2025

Agentic AI in Healthcare:
Navigating Risks, Realizing Benefits

AICU

: Adaptive Intelligence for Dynamic Patient Monitoring in ICU

Team. G	2025.10.18

BACKGROUD

The Reality of Intensive Care Units care

The ICU treats critically ill patients whose conditions change rapidly, making **continuous monitoring essential**.

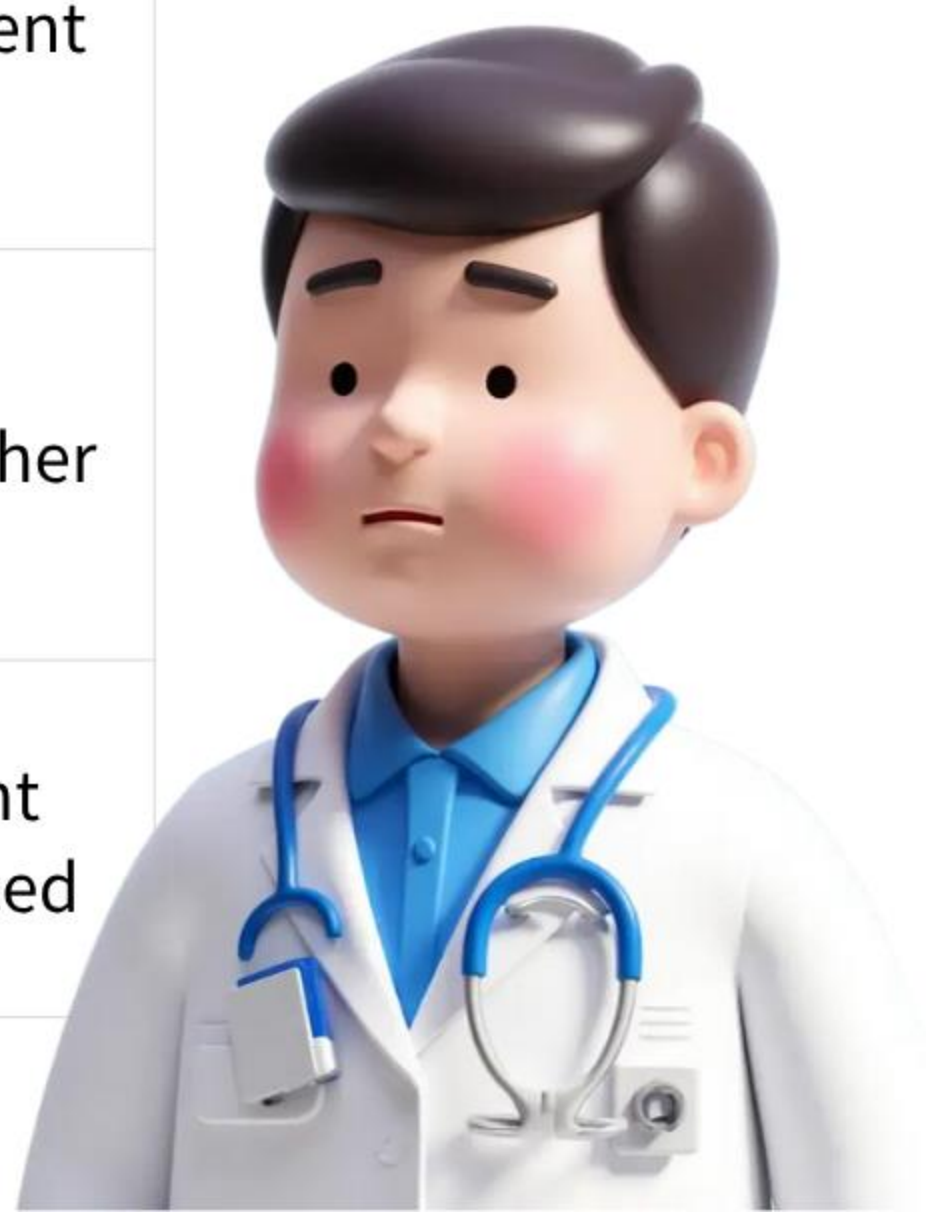
However,
each clinician **oversees multiple patients**, and **hundreds of vital signs and lab results** stream in every minute.

This leads to information **overload, delayed recognition, and missed critical events.**

STRUCTURAL CHALLENGES IN THE ICU

High-density environment can cause clinical impact

Category	What happens	Clinical impact
Static Scoring Systems	Conventional scores (SOFA, APACHE, etc.)	Delayed detection of patient deterioration
Information Overload	Hundreds of real-time vital, lab, and medication data	Missed critical signals, increased fatigue, and higher risk of error
Non-adaptive to Repeated Data	Repetitive lab results	Subtle changes in patient trajectory remain unnoticed



STRUCTURAL CHALLENGES IN THE ICU

High-density environment can cause clinical impact

Category	What happens
Static Scoring Systems	Conventional scores (SOF

It shows where the patient is,

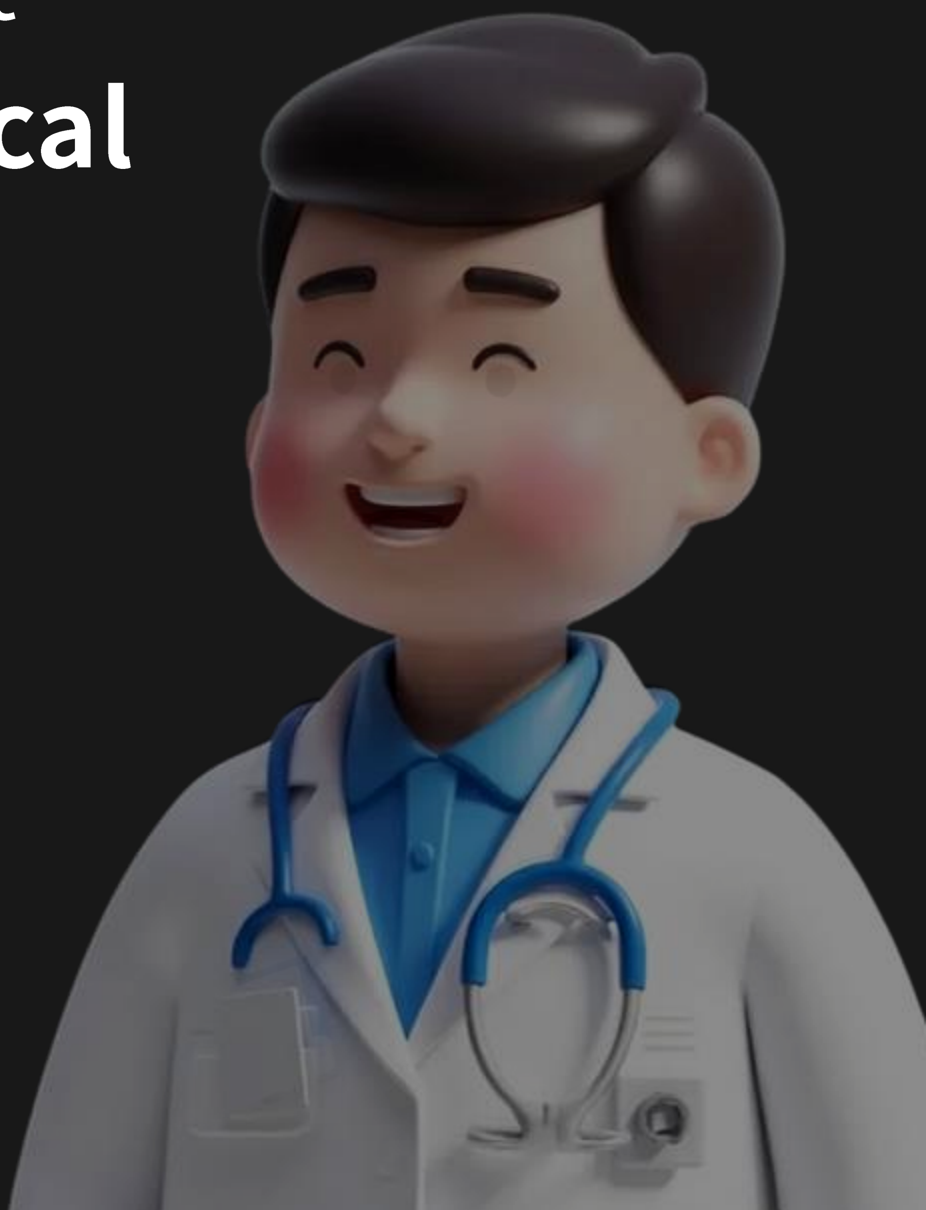
not where the patient is heading.

STRUCTURAL CHALLENGES IN THE ICU

High-density environment can cause clinical impact

Category	What happens
Static Scoring Systems	APACHE, etc.)

Develop an **intelligent, dynamic monitoring system** that tracks patient stage and prognosis, **identifies key clinical features, and supports timely, data-driven decision-making**.



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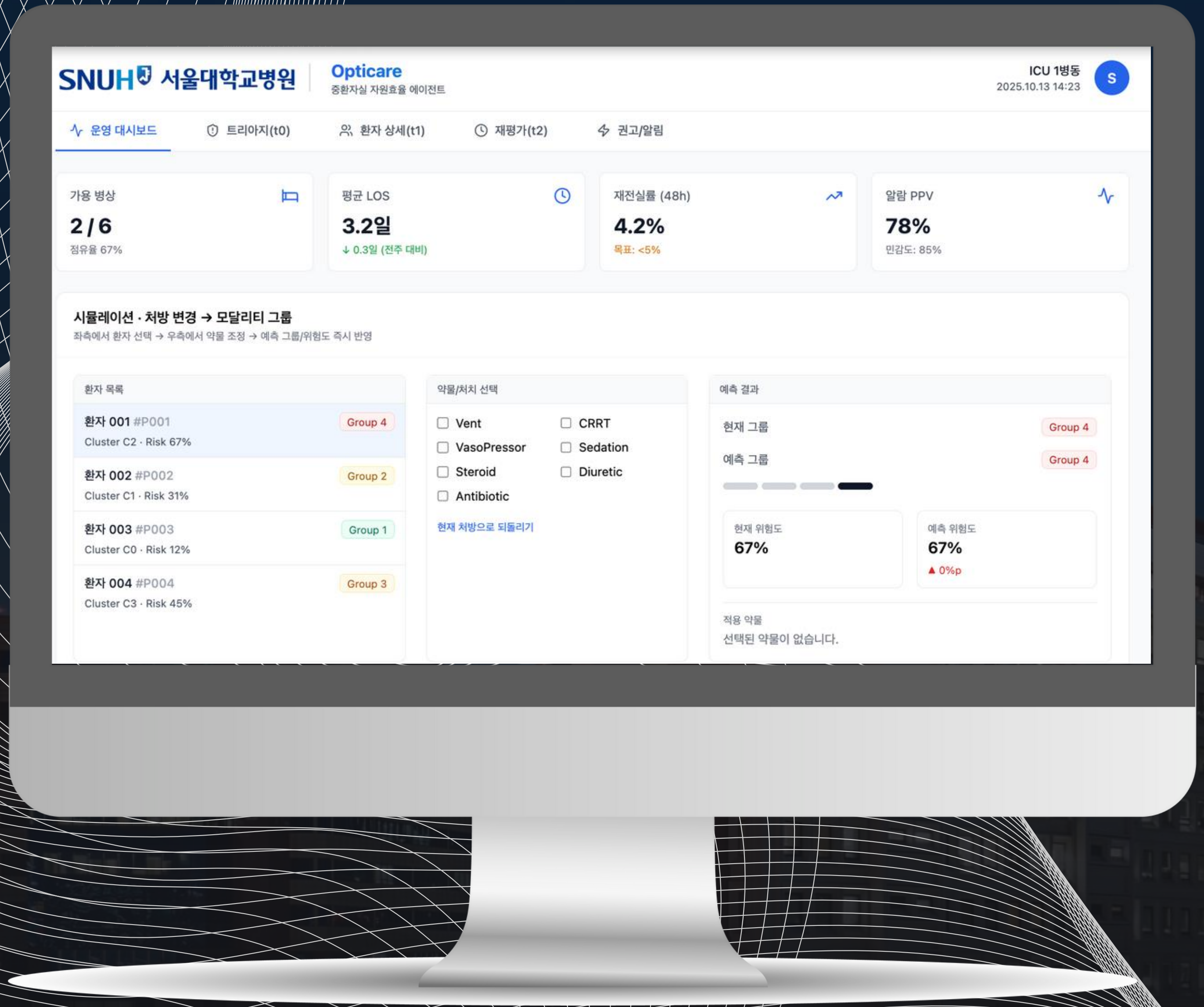
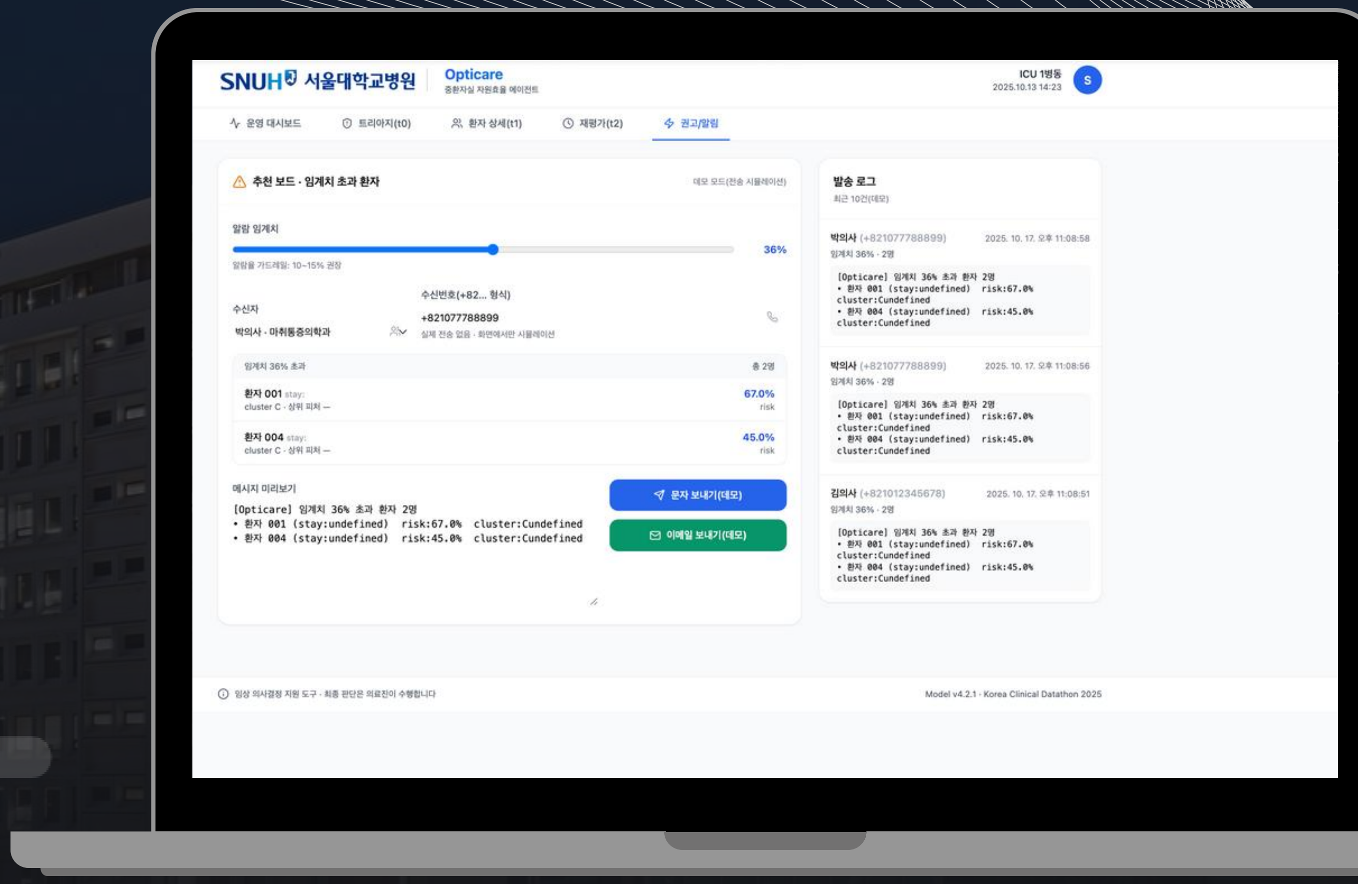
Agentic AI in Healthcare:
Navigating Risks, Realizing Benefits

AICU

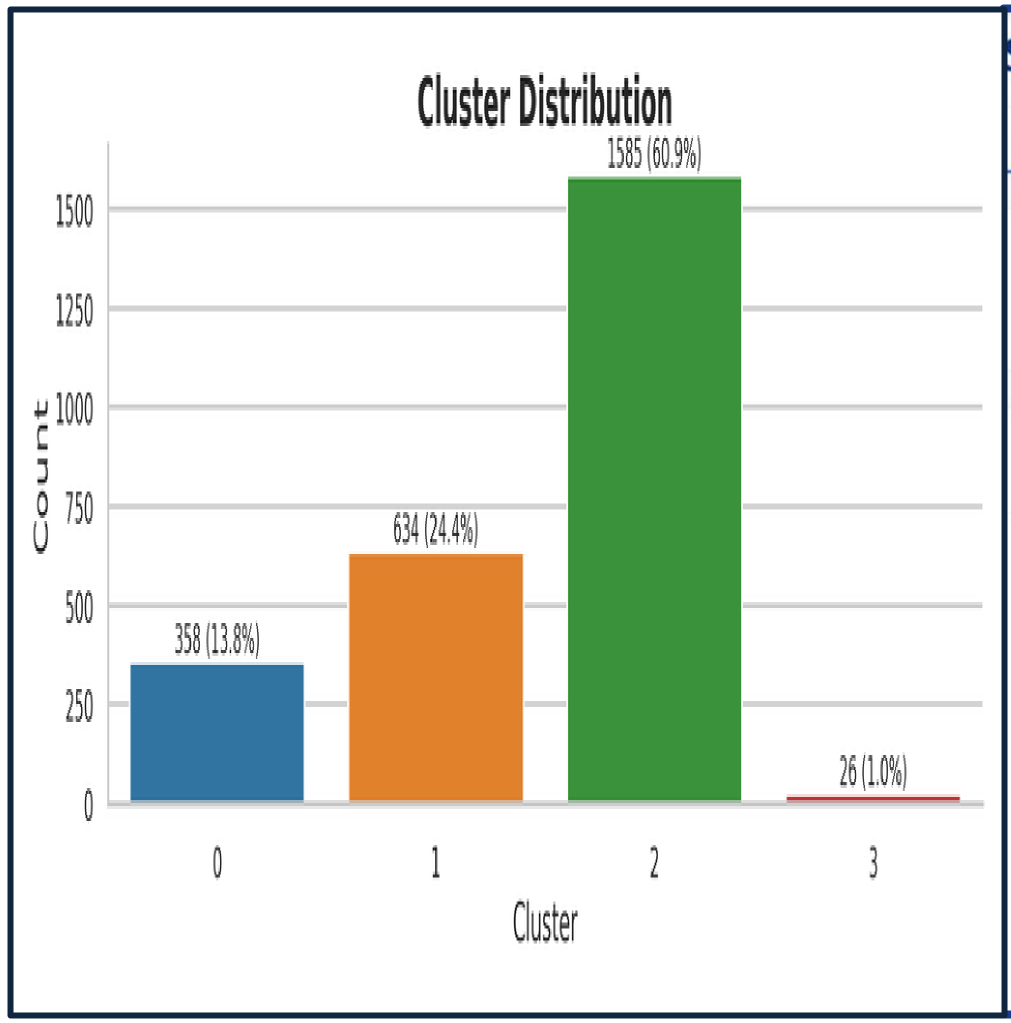
An ICU resource-efficiency agent that predicts risk, manages alert thresholds, and guides bed allocation across the patient journey





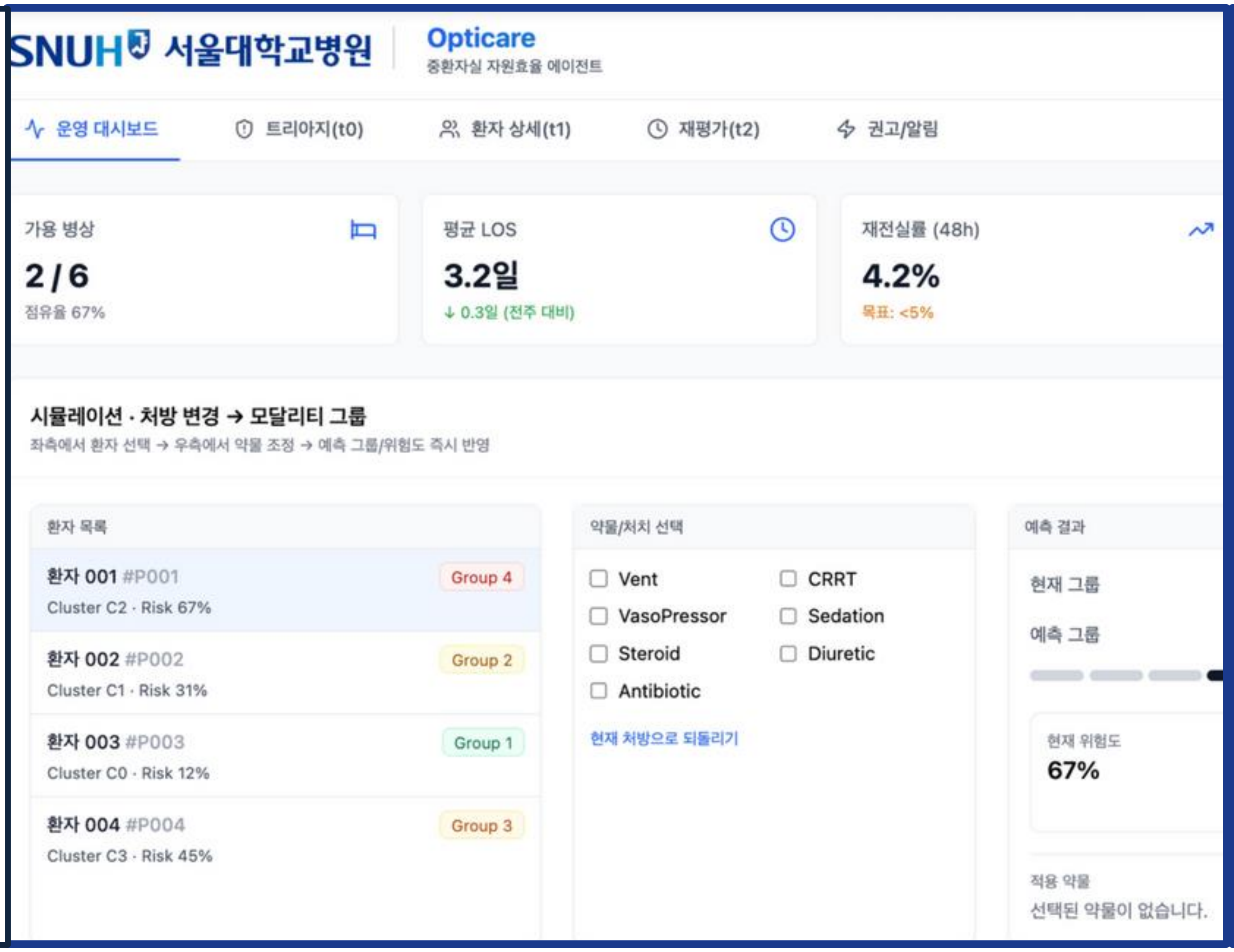
OUR GOAL: INTELLIGENT, DYNAMIC, PATIENT MONITORING SYSTEM

Main Features



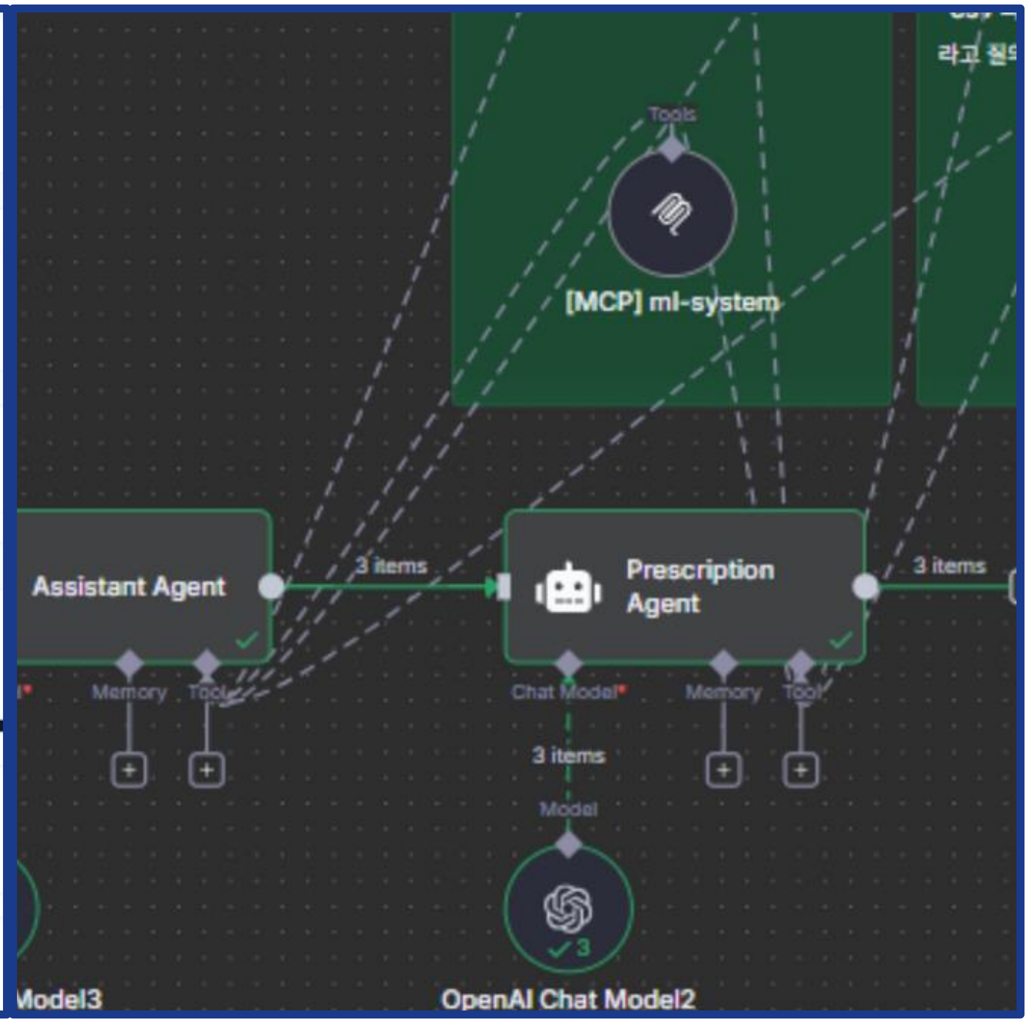
Adaptive Patient Clustering

Unsupervised clustering automatically groups patients by severity and physiological patterns.



Interactive Visualization Dashboard

Displays cluster-level trends, key features, and survival curves in an intuitive view.

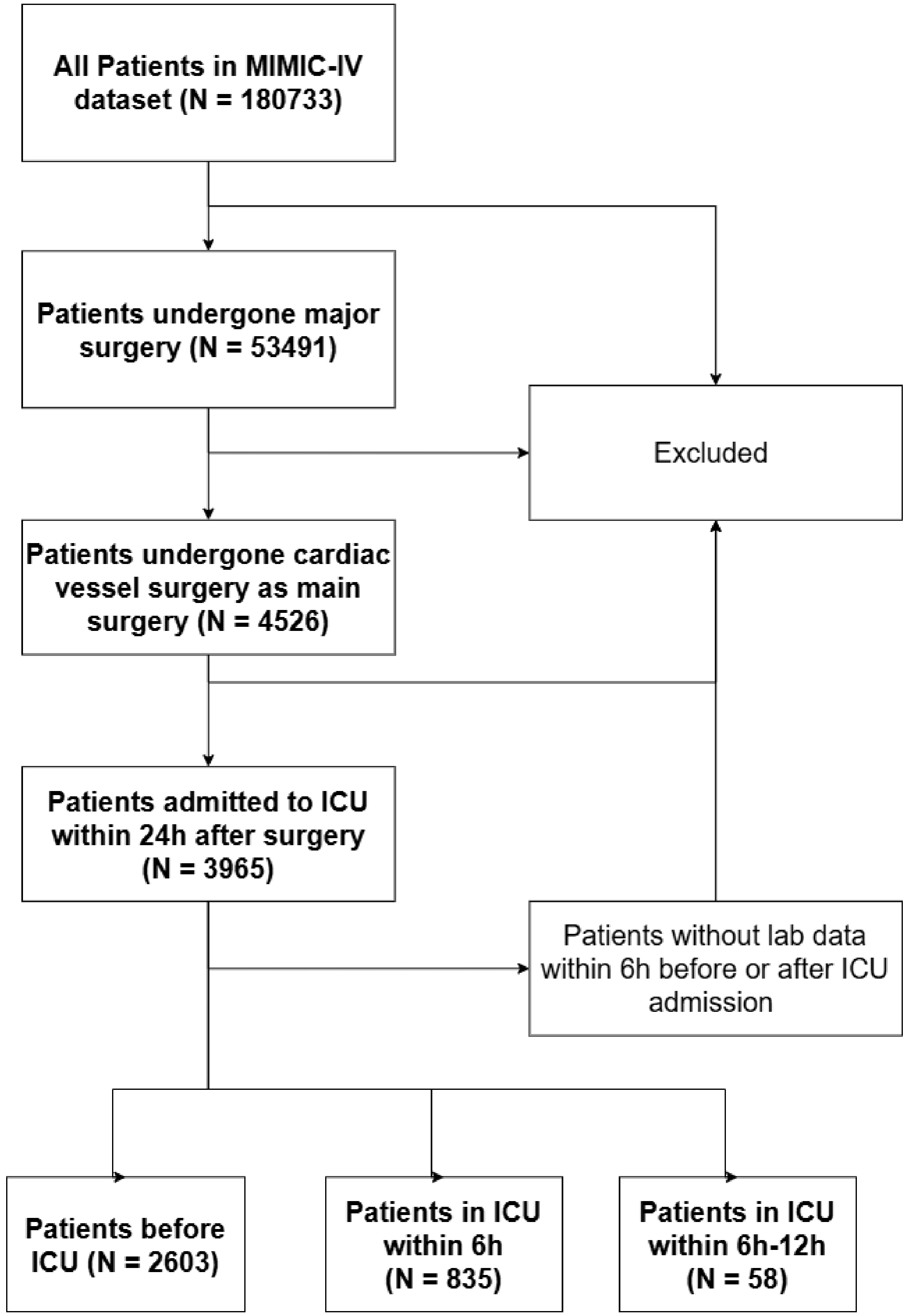


LLM-powered Briefing Agent

Periodically summarizes key updates and delivers concise daily/weekly briefings to clinicians.

DATASET OVERVIEW

Post-op ICU cohort in MIMIC-IV overview



- All Patients in MIMIC-IV dataset (N = 180733)
- Patients undergone major surgery (N = 53491)
  - exclude patients only received medical or minor surgical procedure (by ICD-9 and -10 procedure code)
- Patients undergone cardiac vessel surgery as main surgery (seq_num = 1) (N = 4526)
- Patients admitted to ICU within 24h after surgery (N = 3965)
  - exclude patients with no labs before or after ICU admission

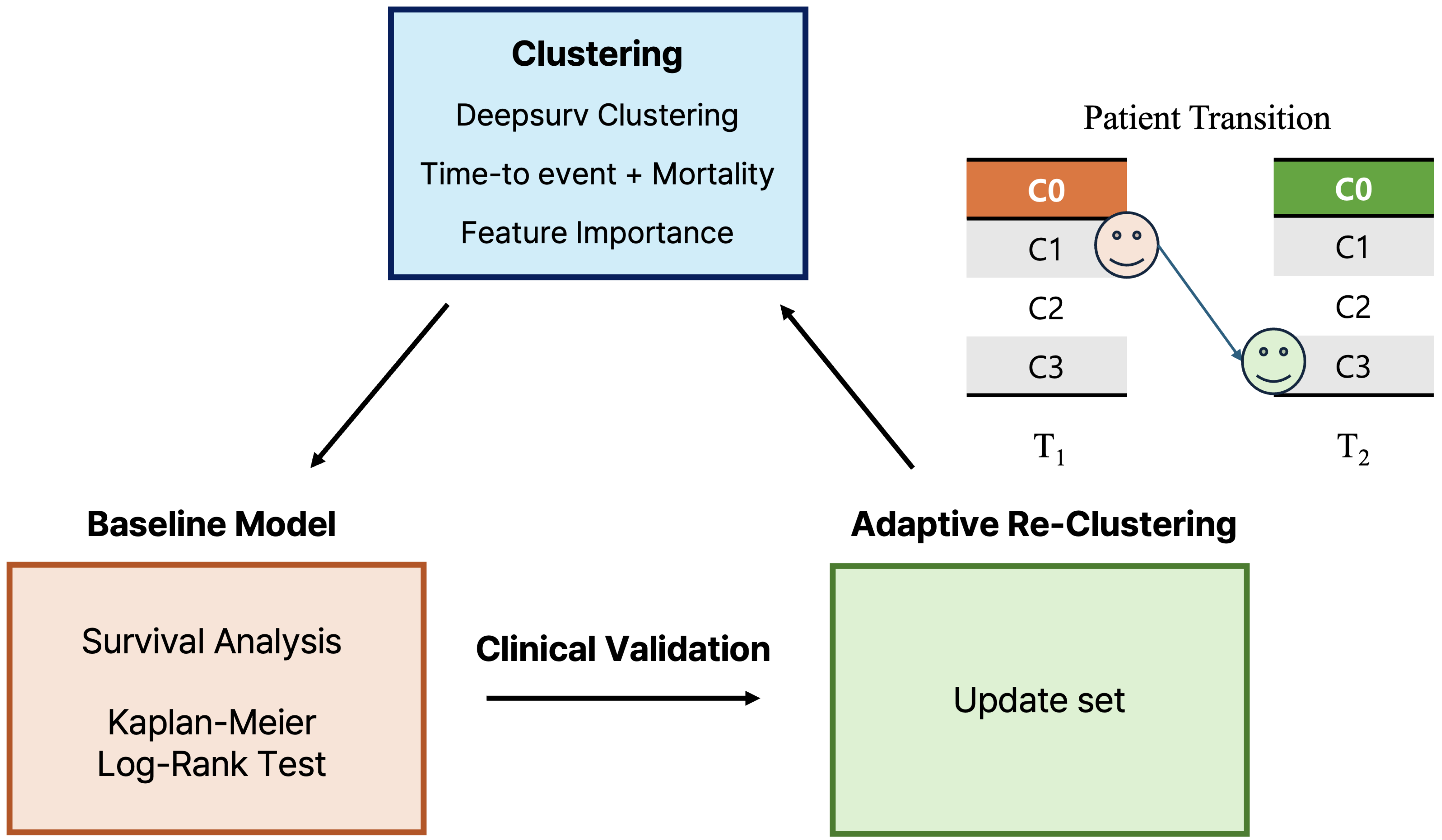
For each patient, two datasets were extracted:

Pre-ICU data (before ICU admission) and In-ICU data (after admission).

METHODS

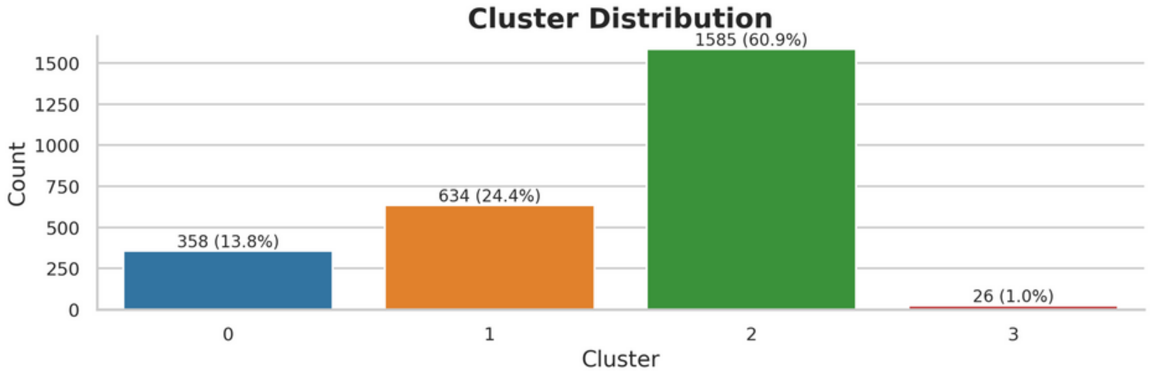
Overall pipeline

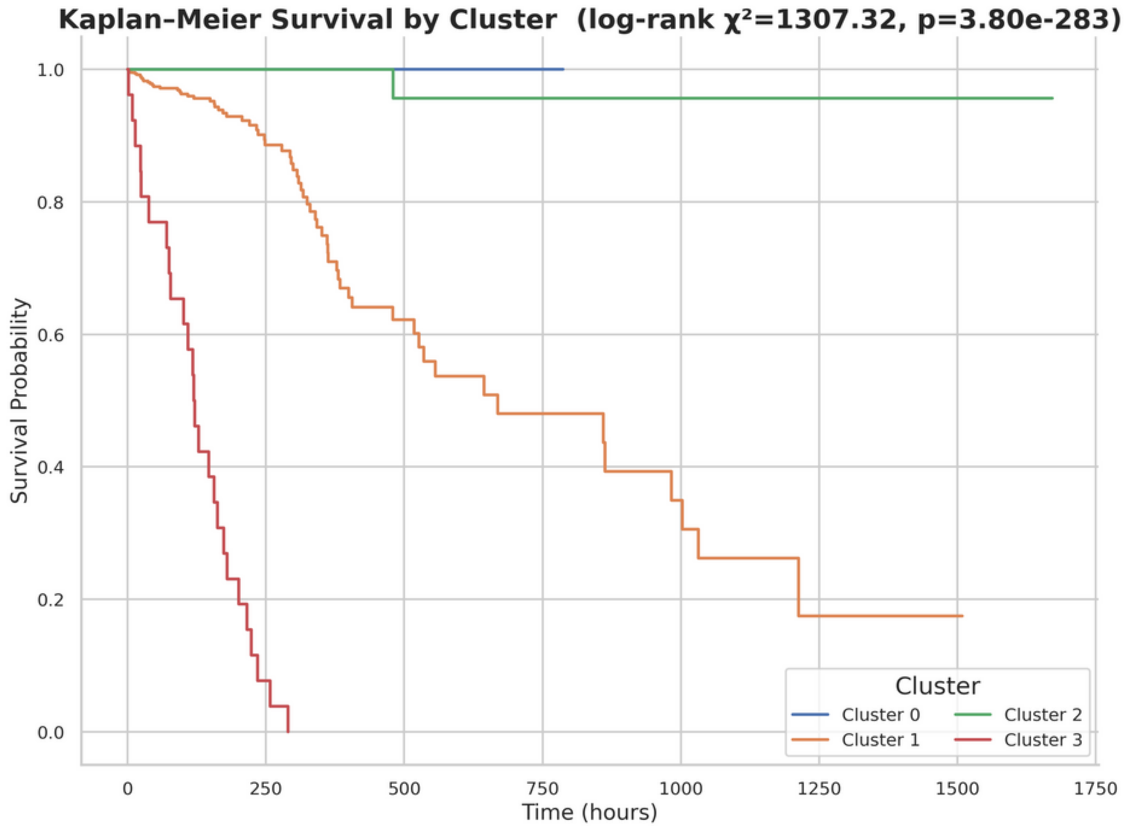
Dynamic cluster updating system

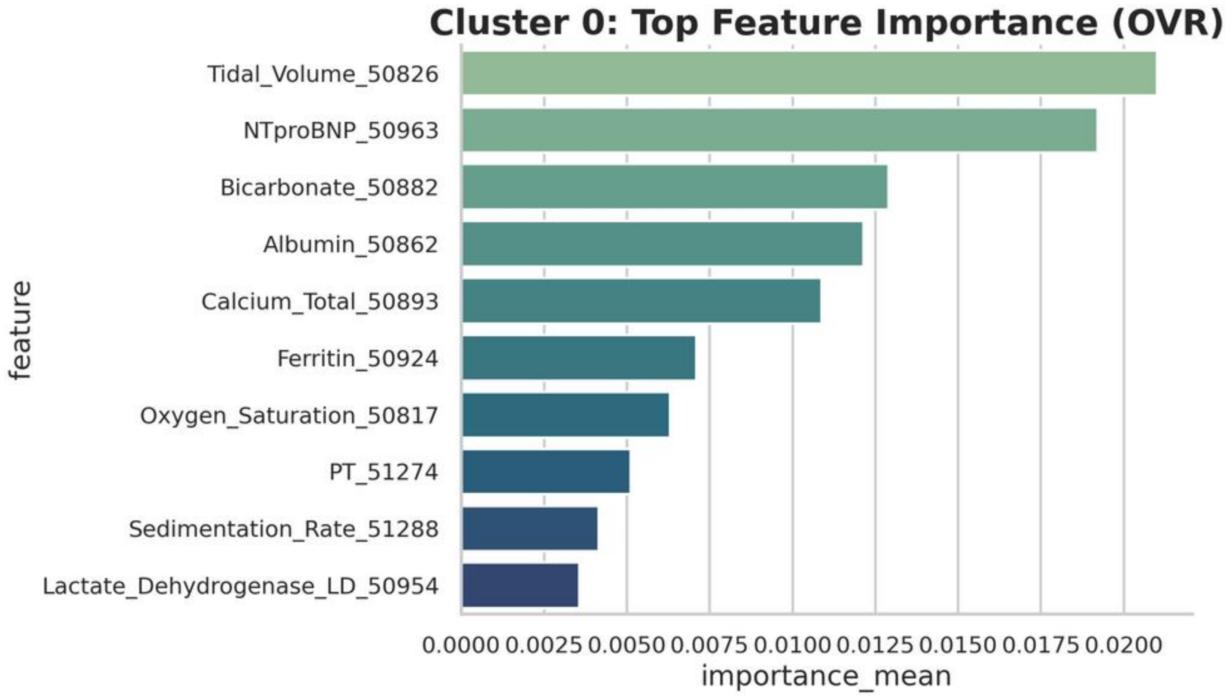


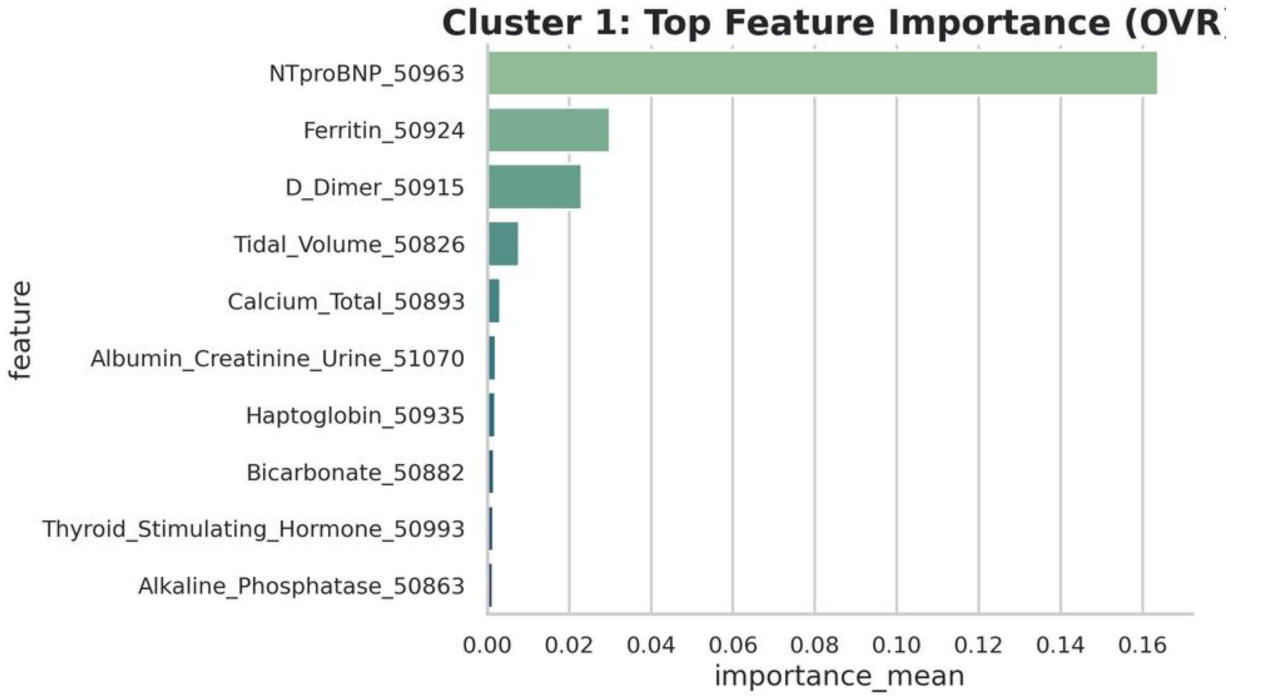
EXPERIMENTS

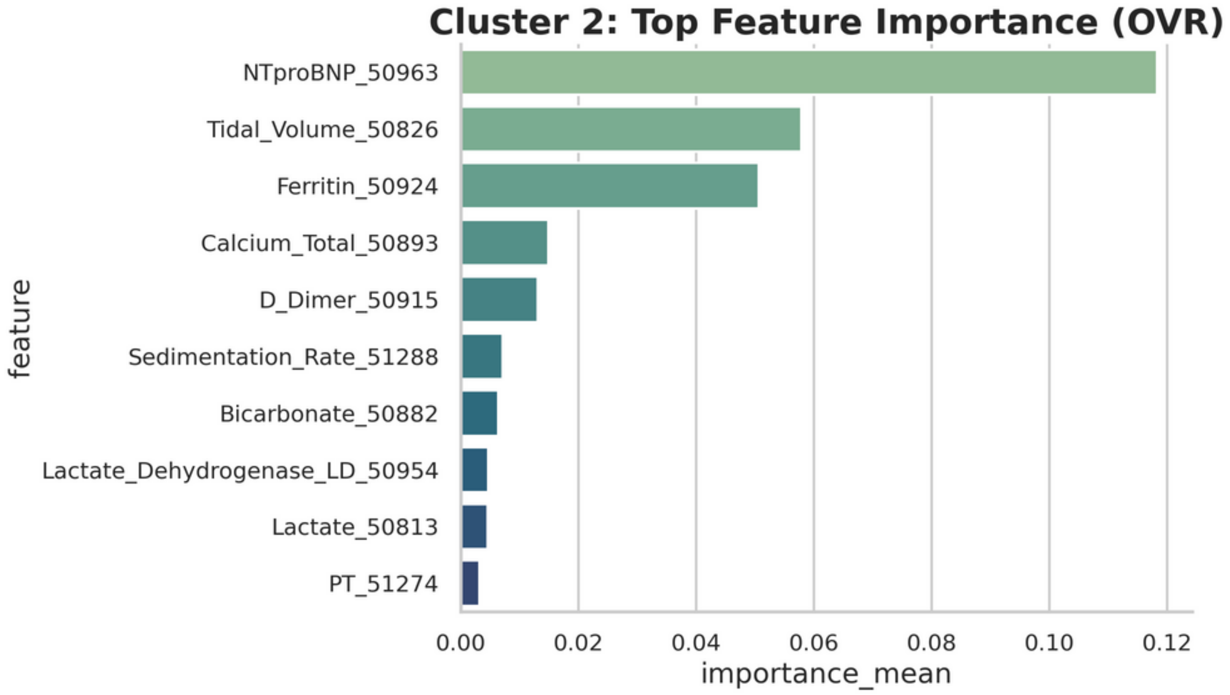
Deepsurv clustering - 1

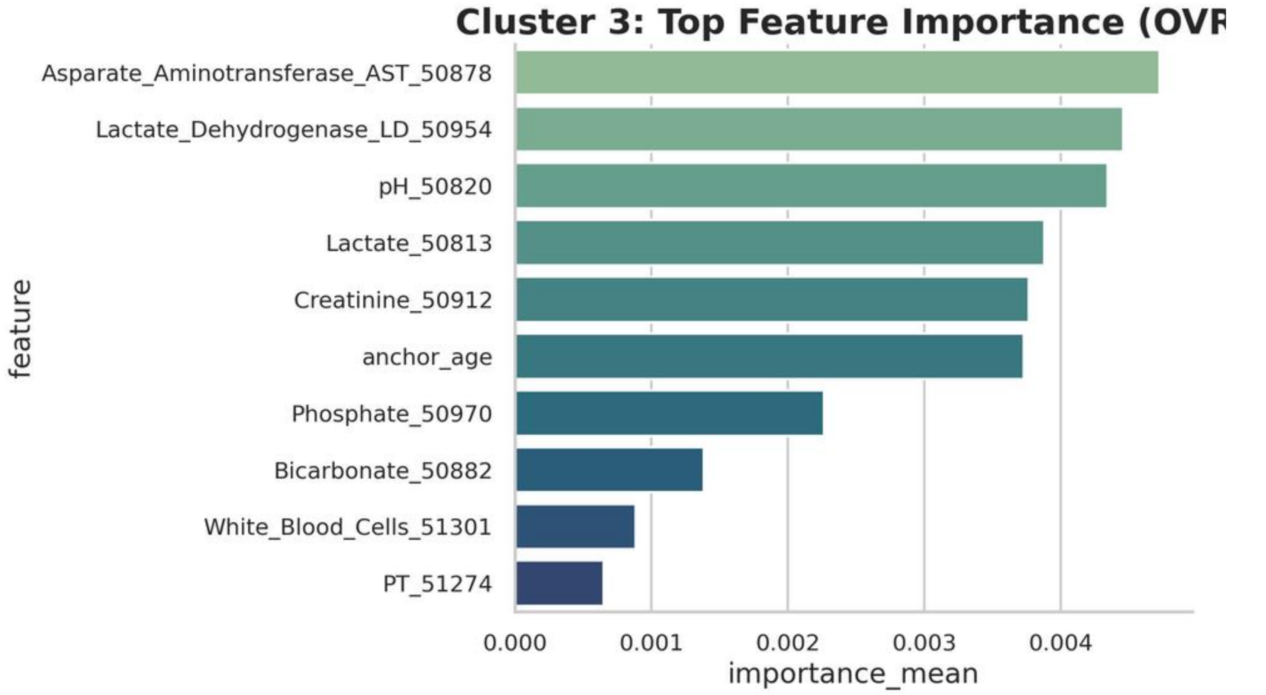






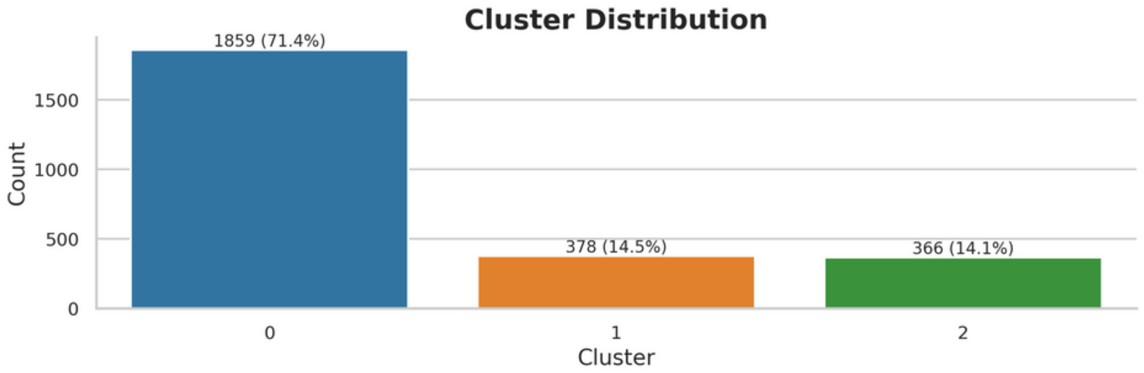


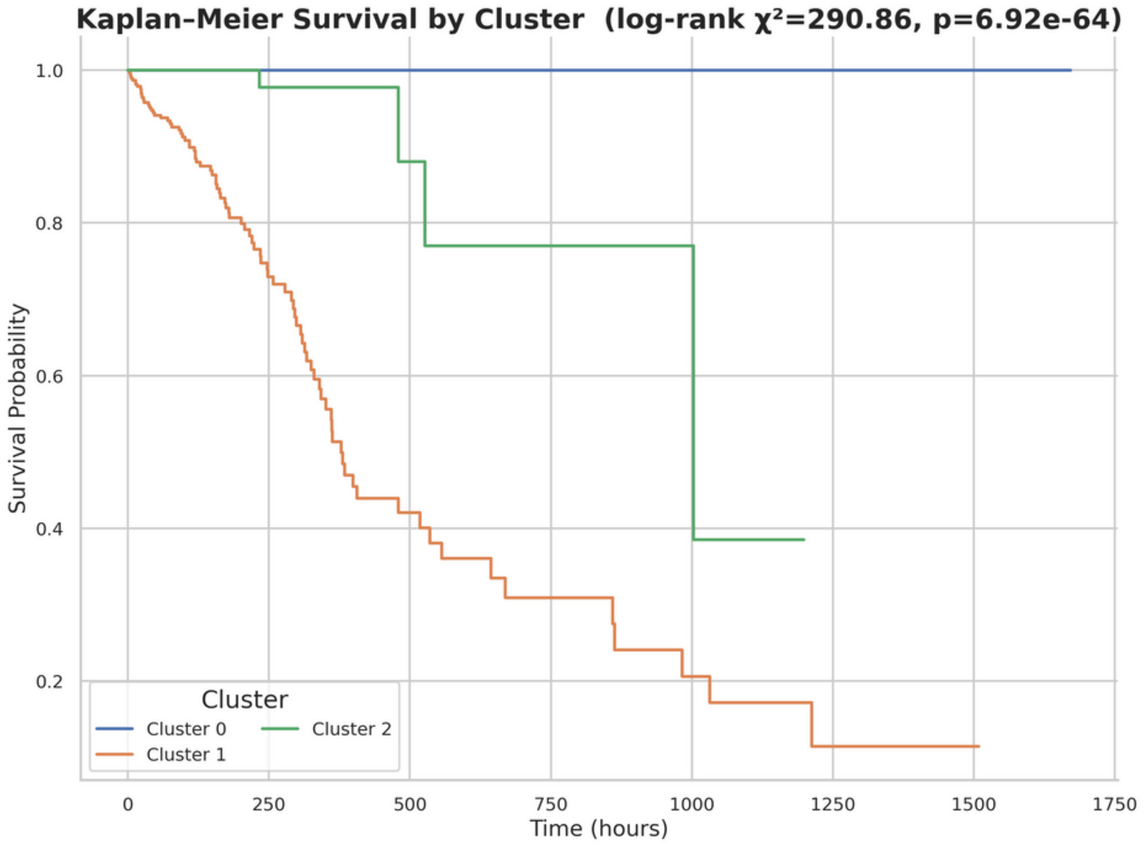


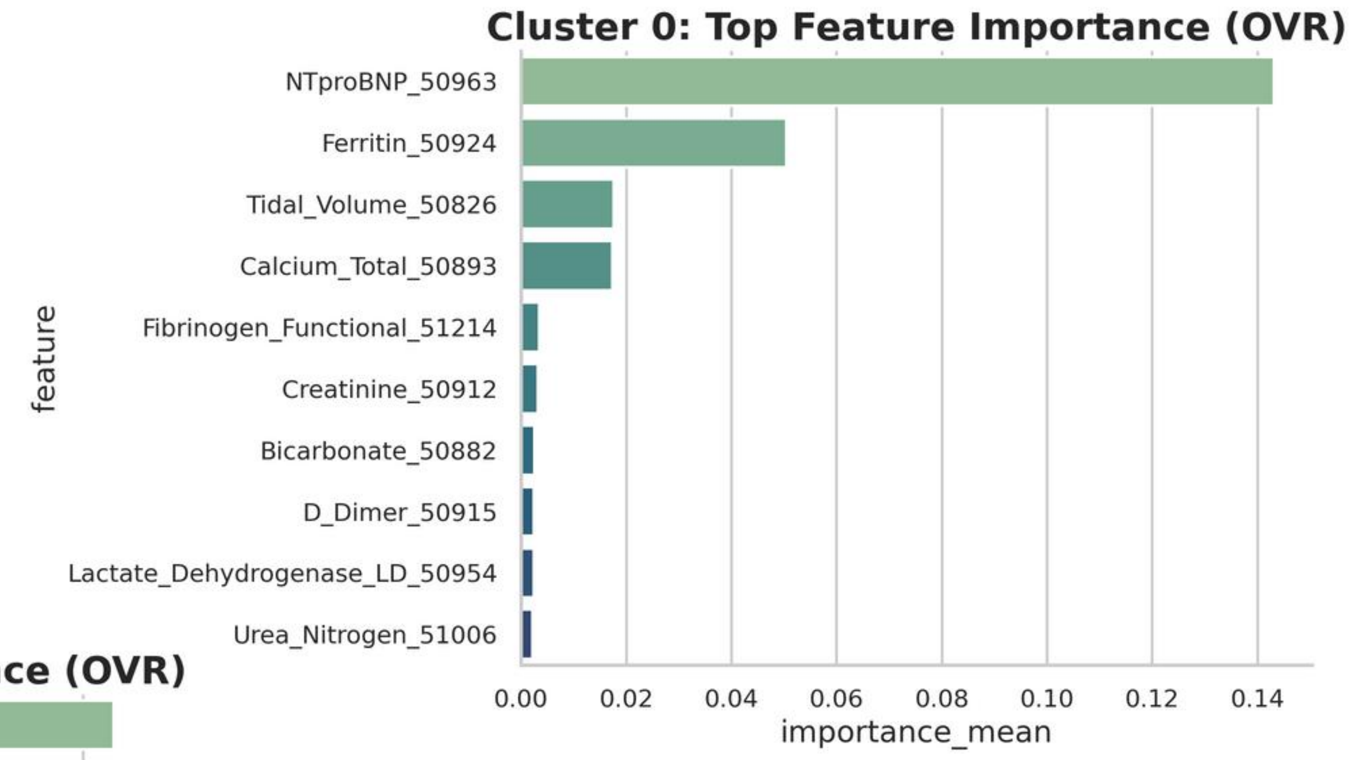


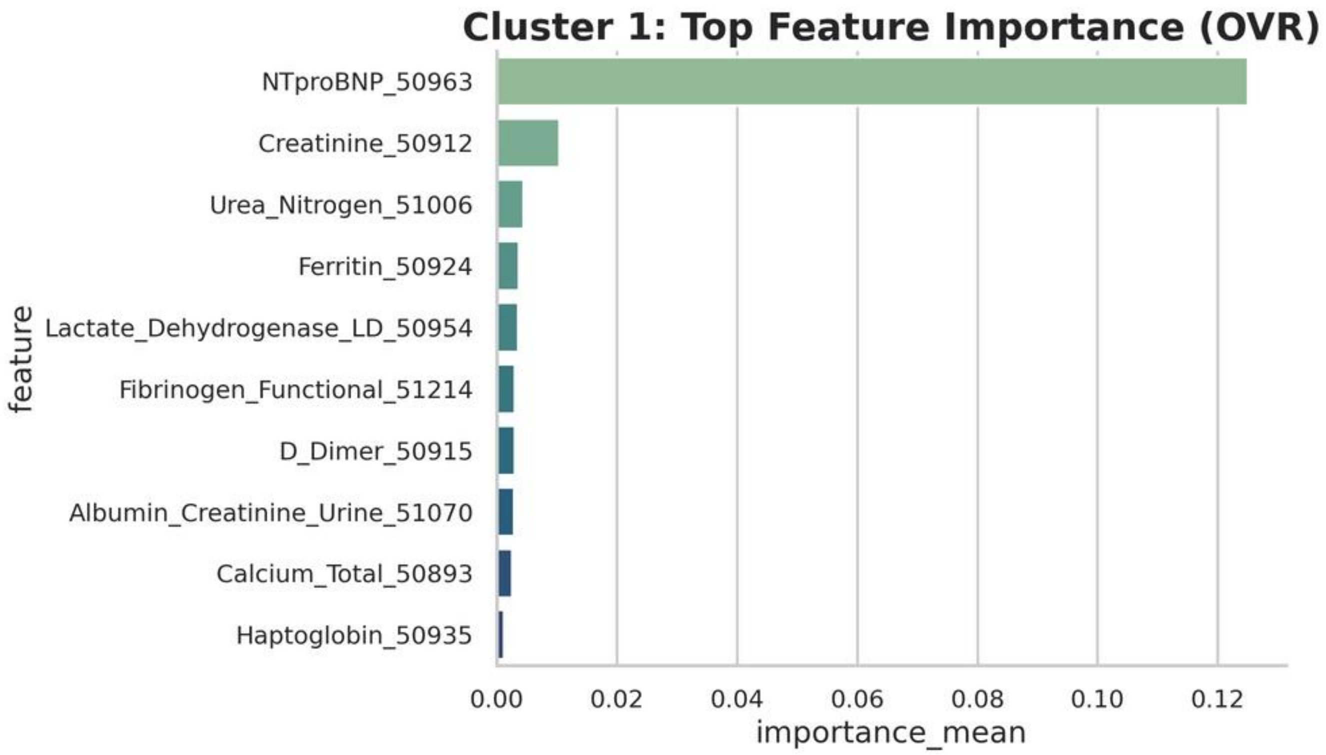
EXPERIMENTS

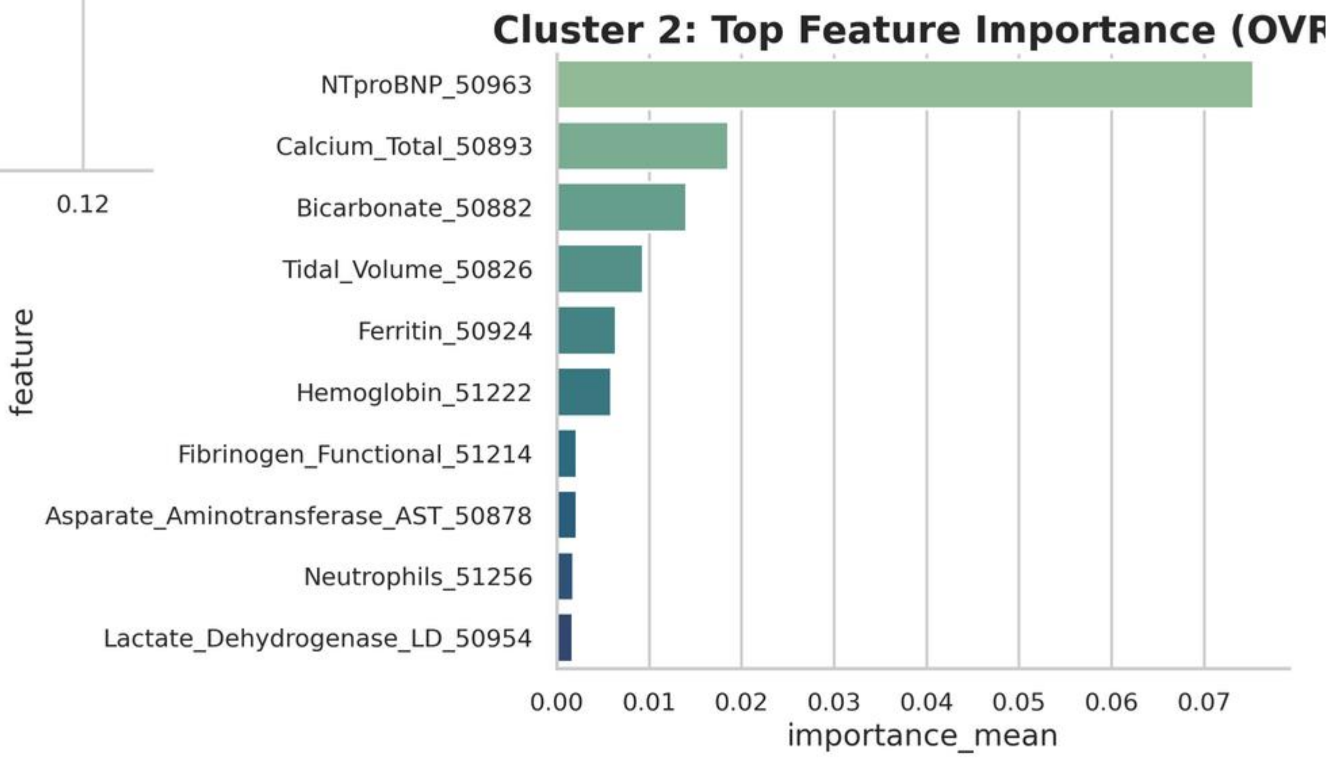
Deepsurv clustering - 2





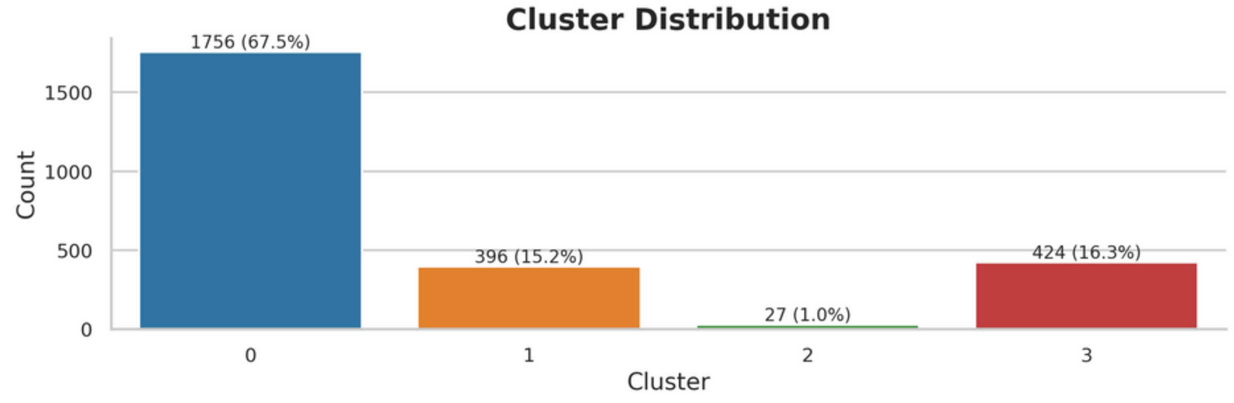


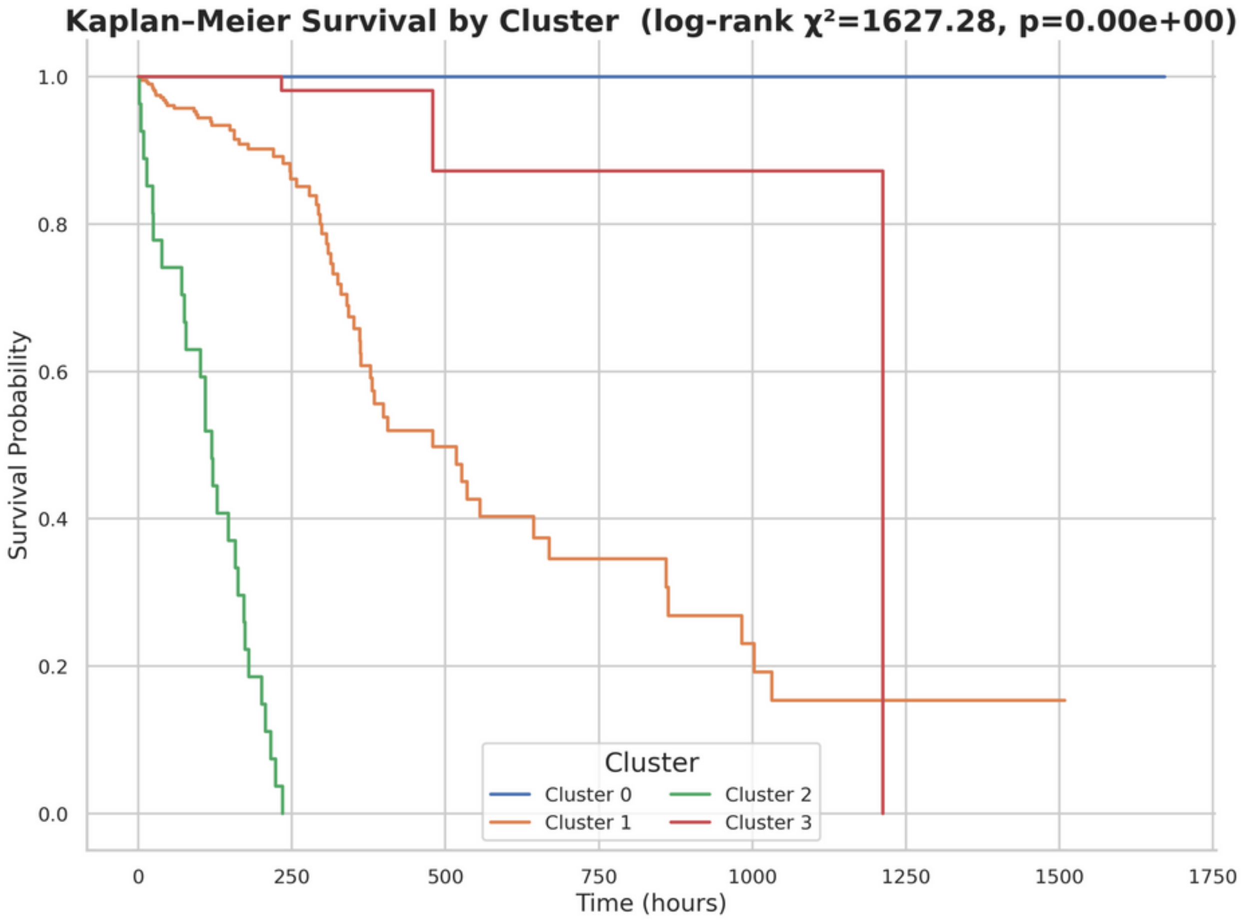


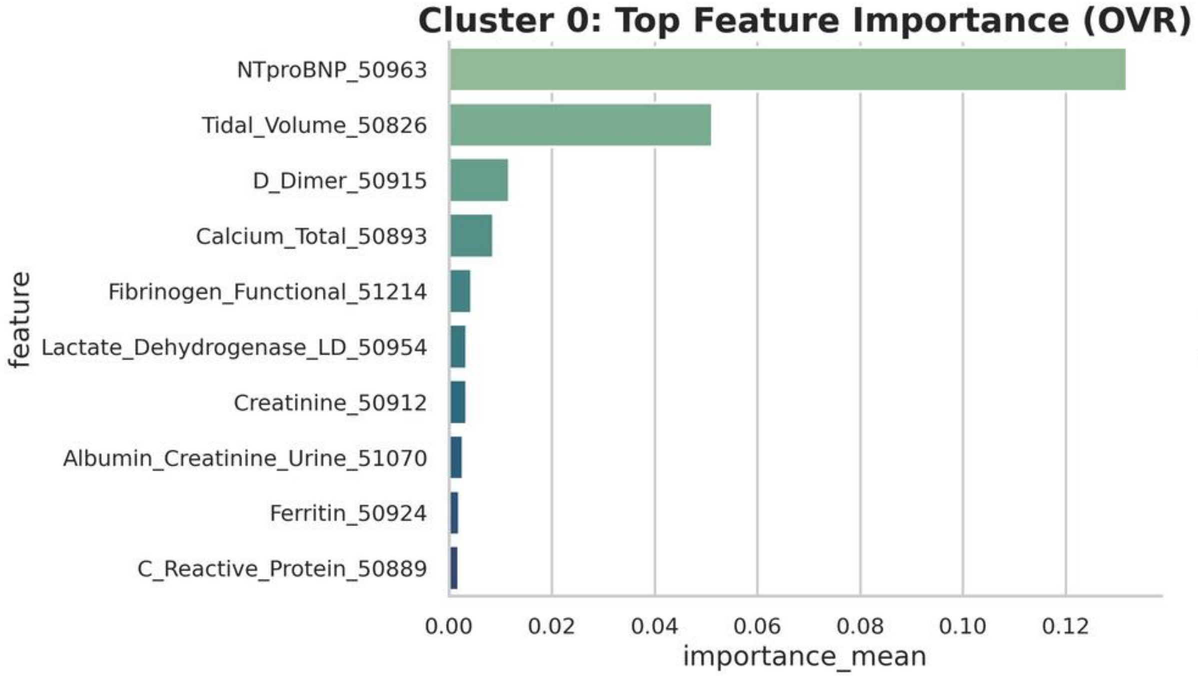


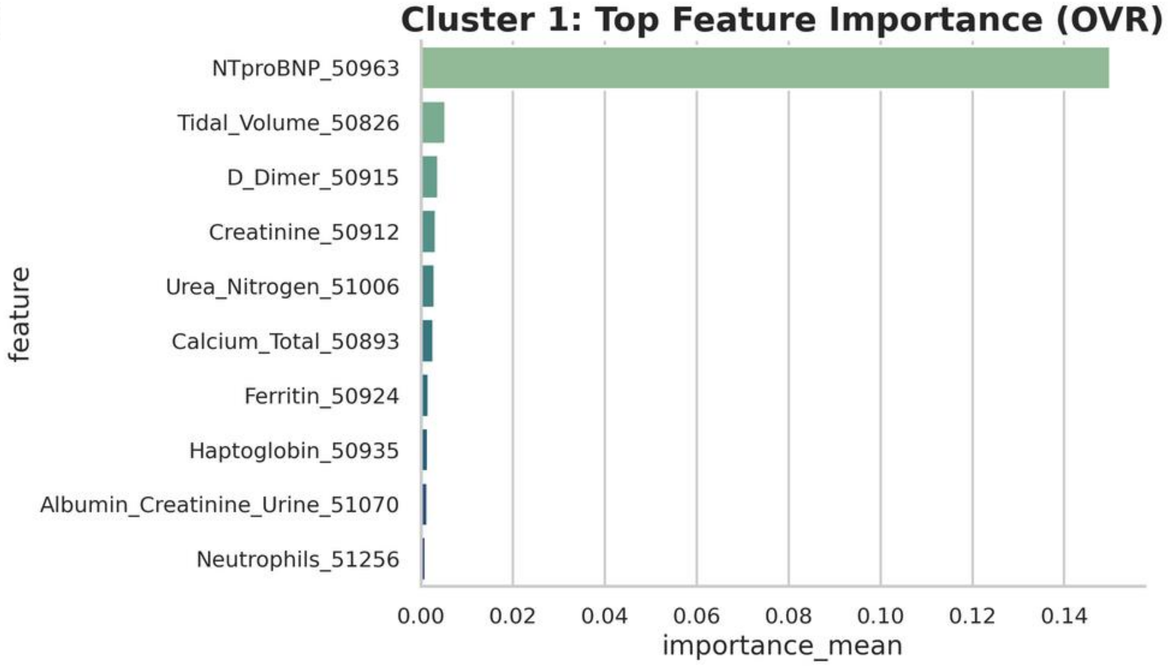
EXPERIMENTS

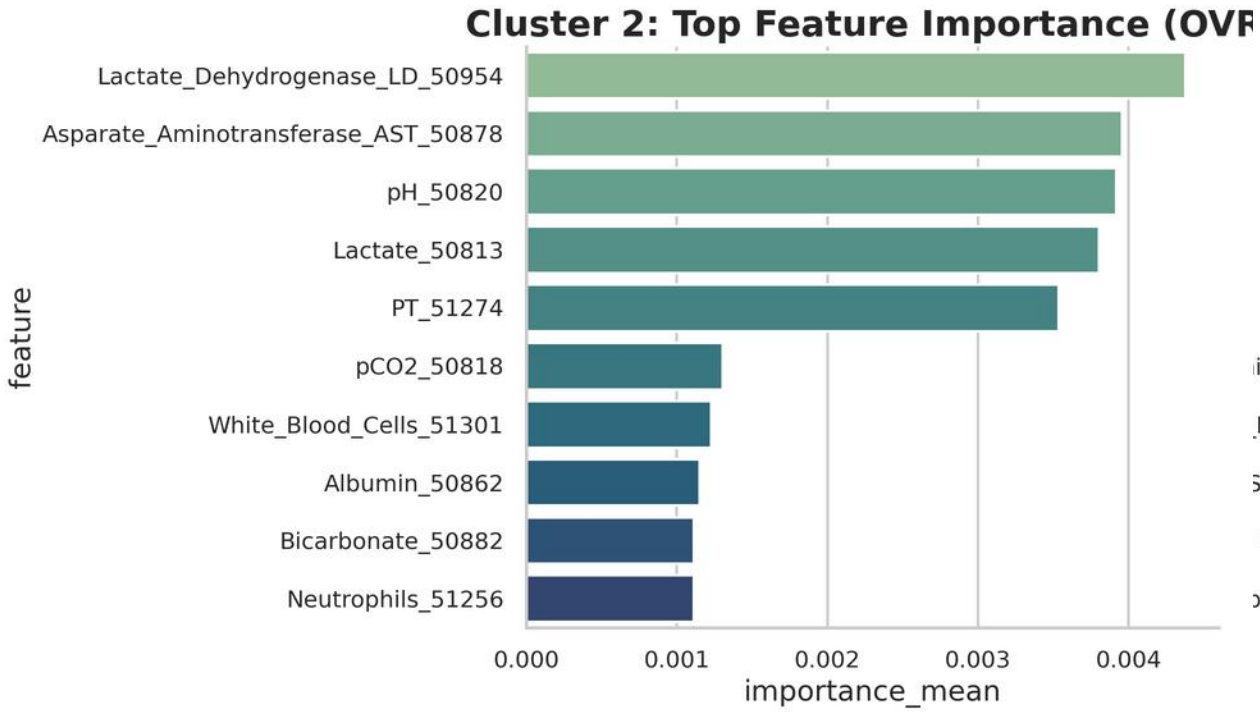
Deepsurv clustering - 3

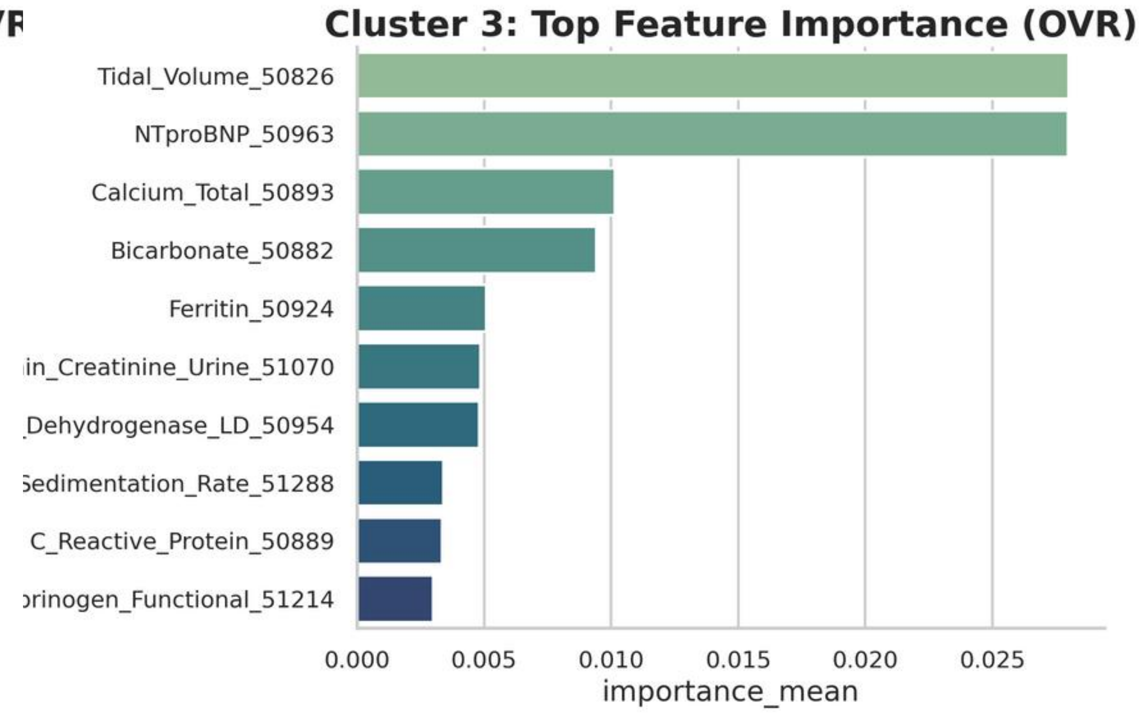






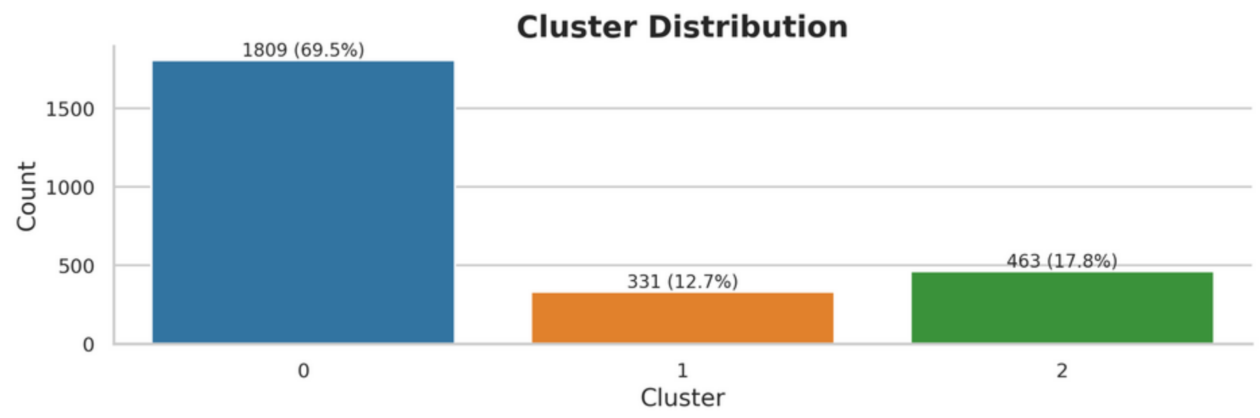


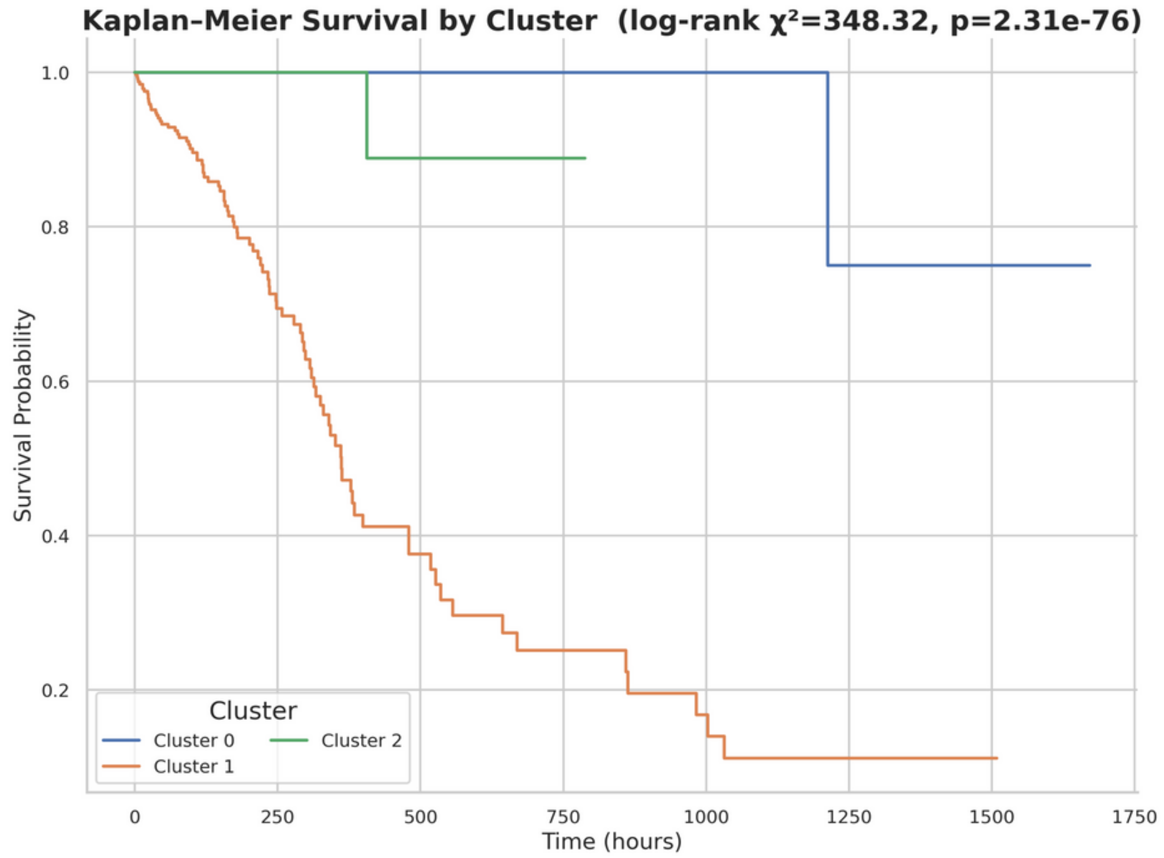


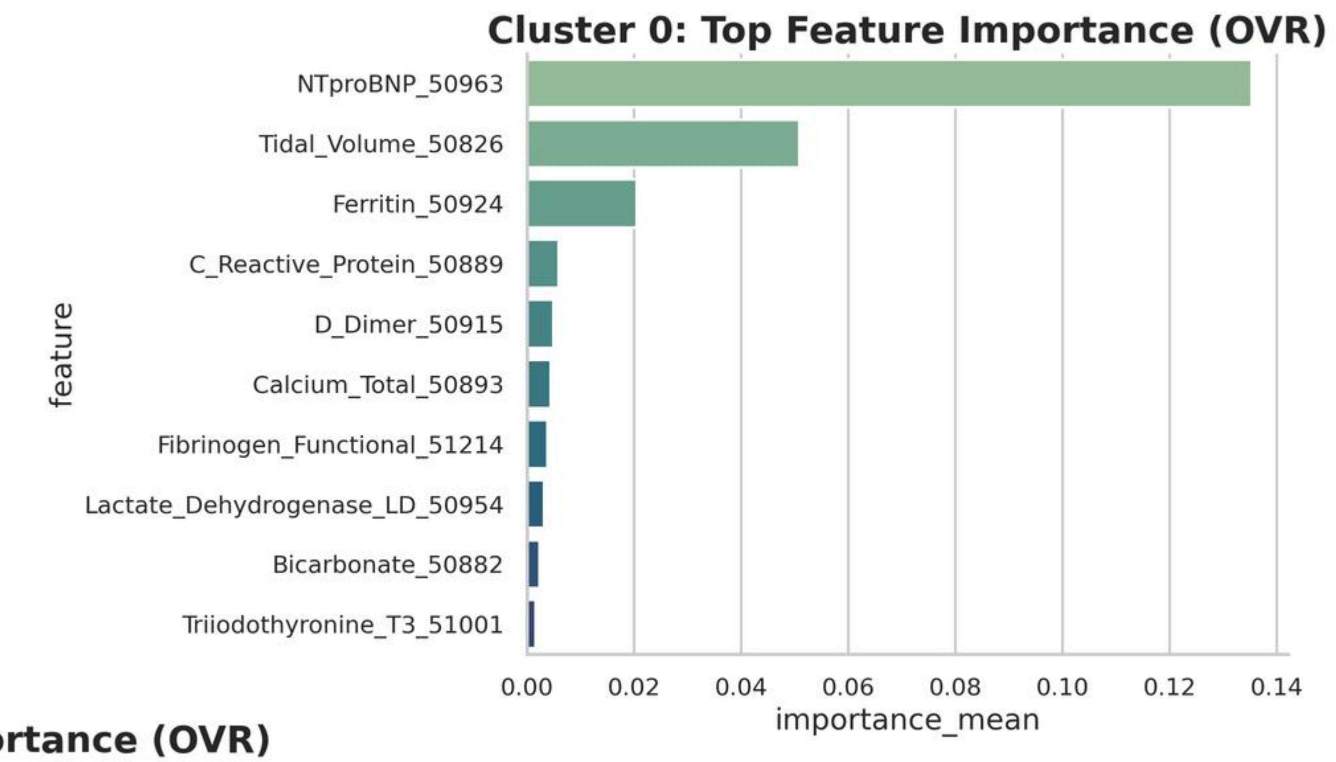


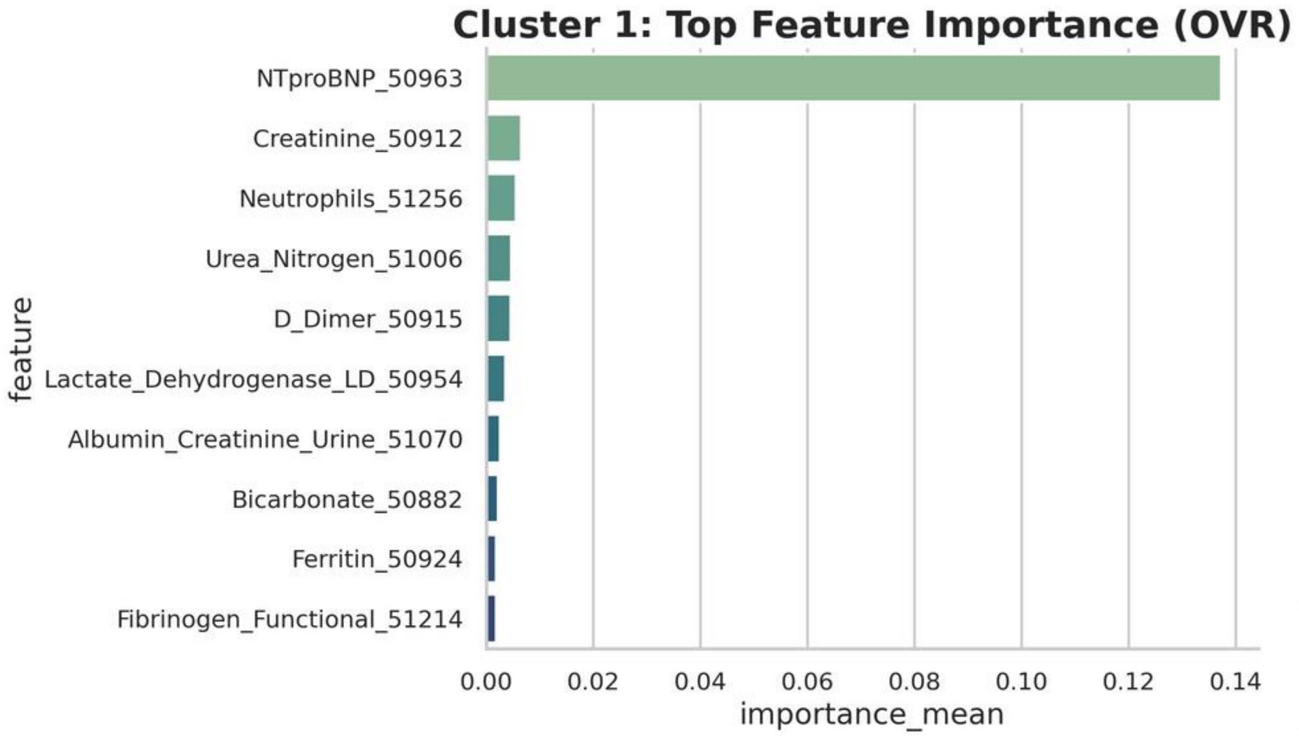
EXPERIMENTS

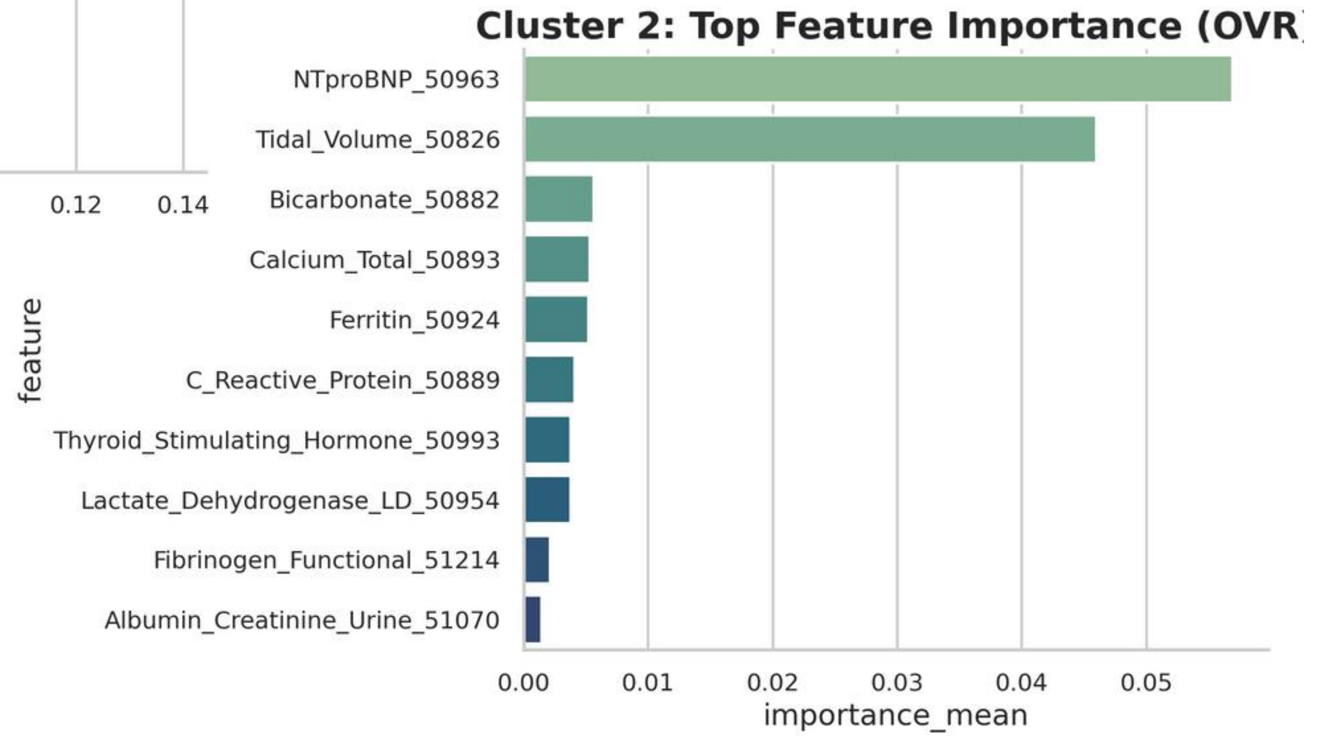
Deepsurv clustering - 4





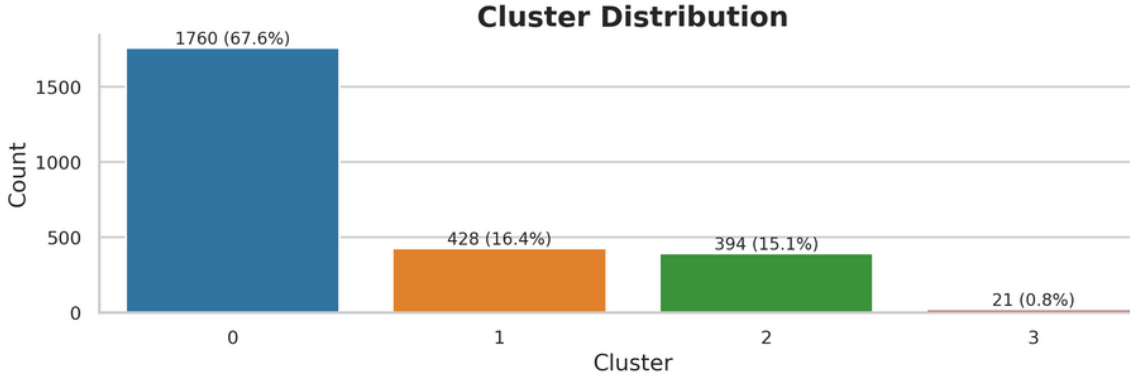


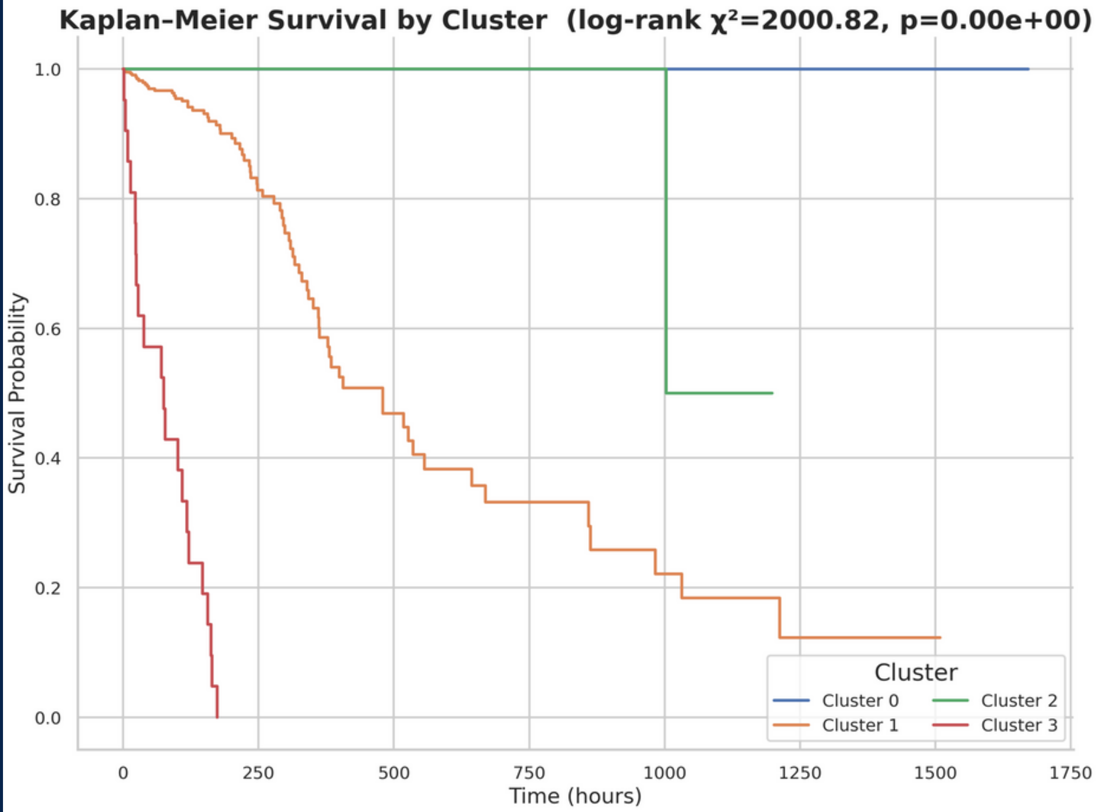


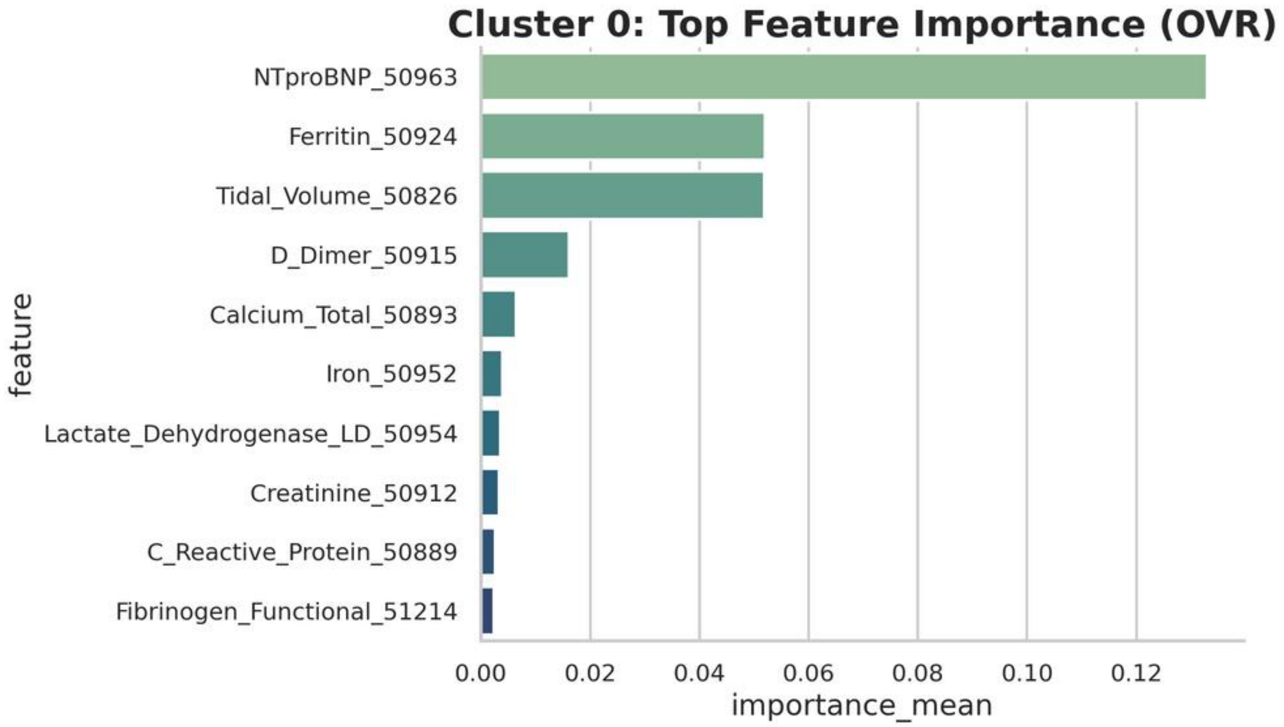


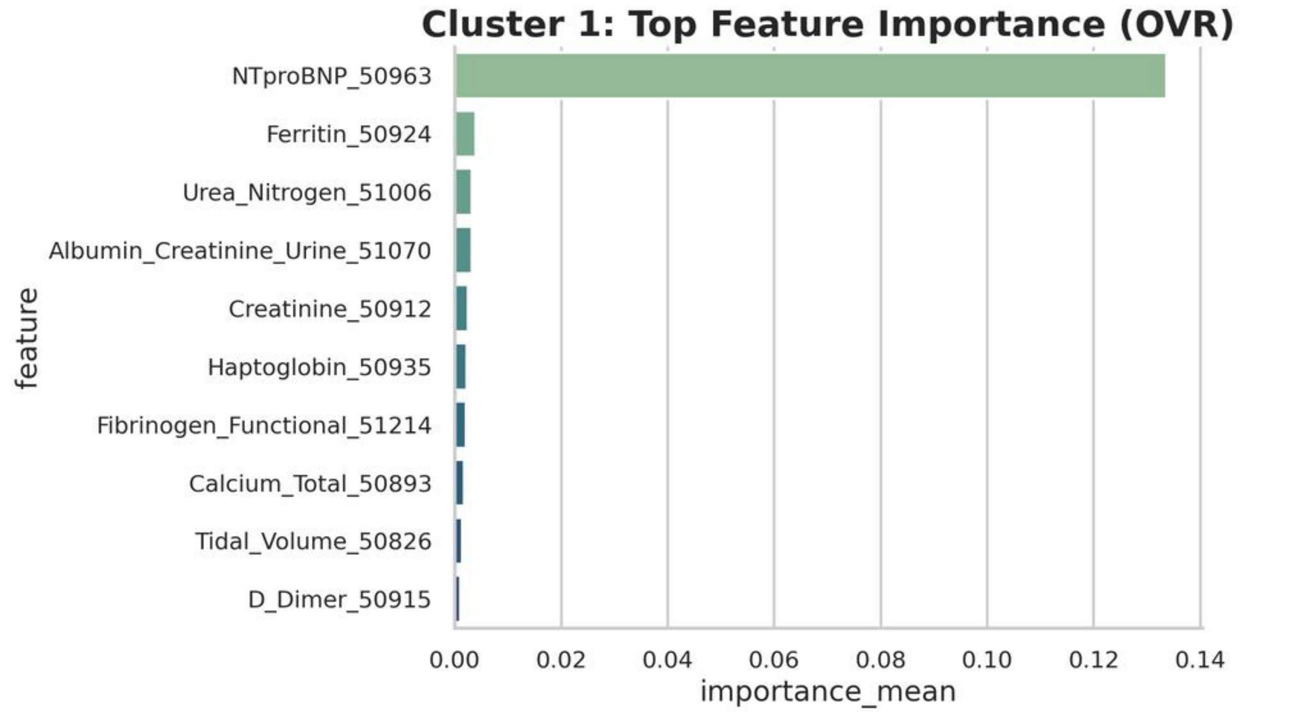
EXPERIMENTS

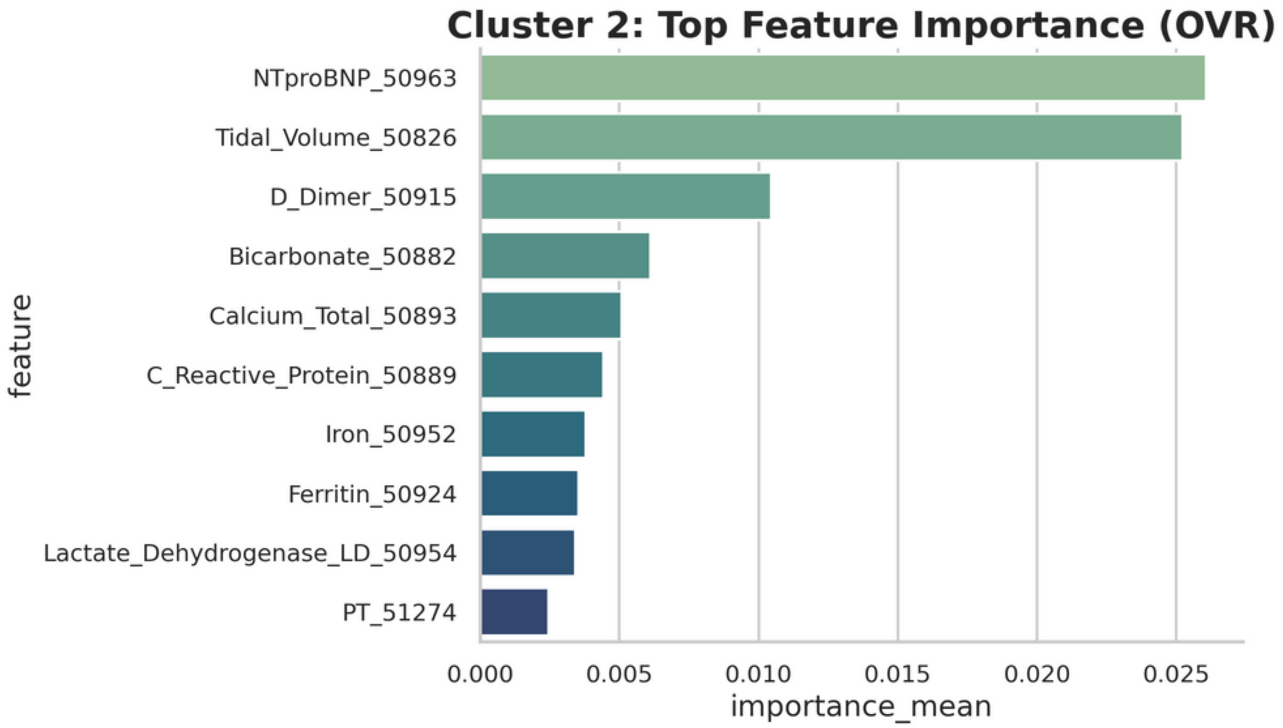
Deepsurv clustering - 5

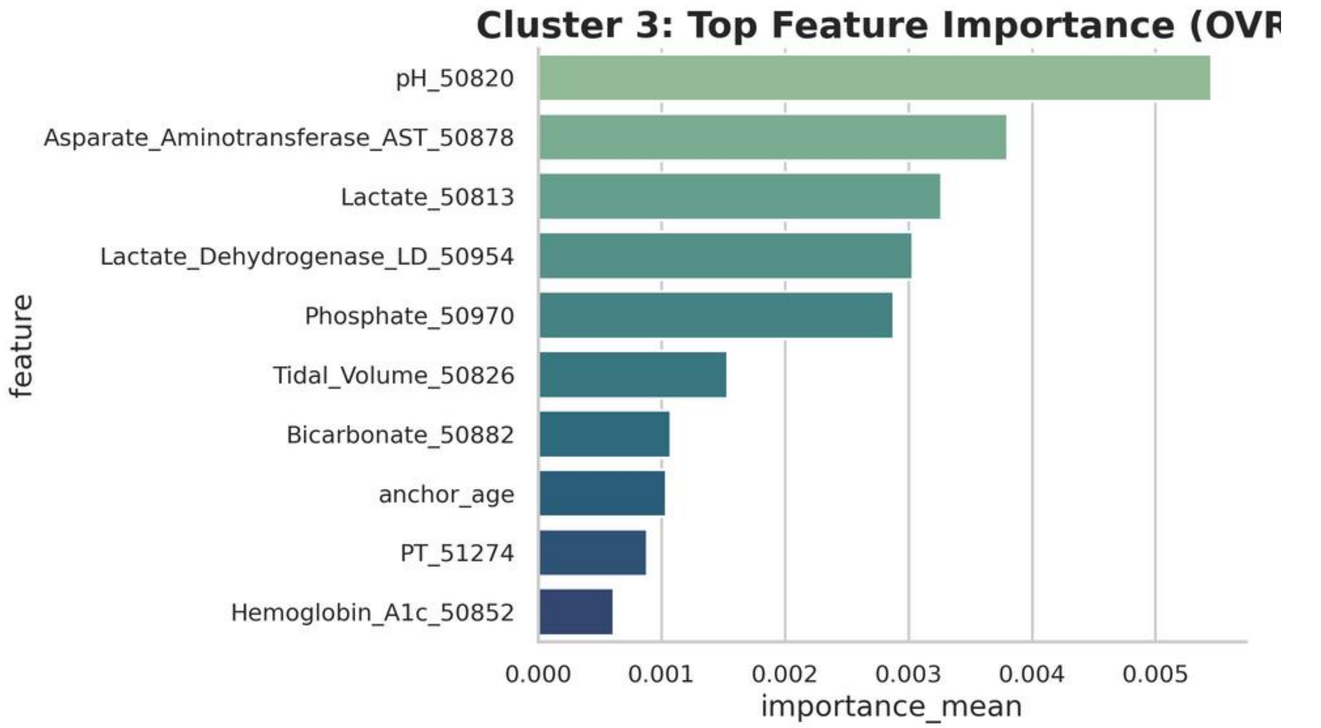






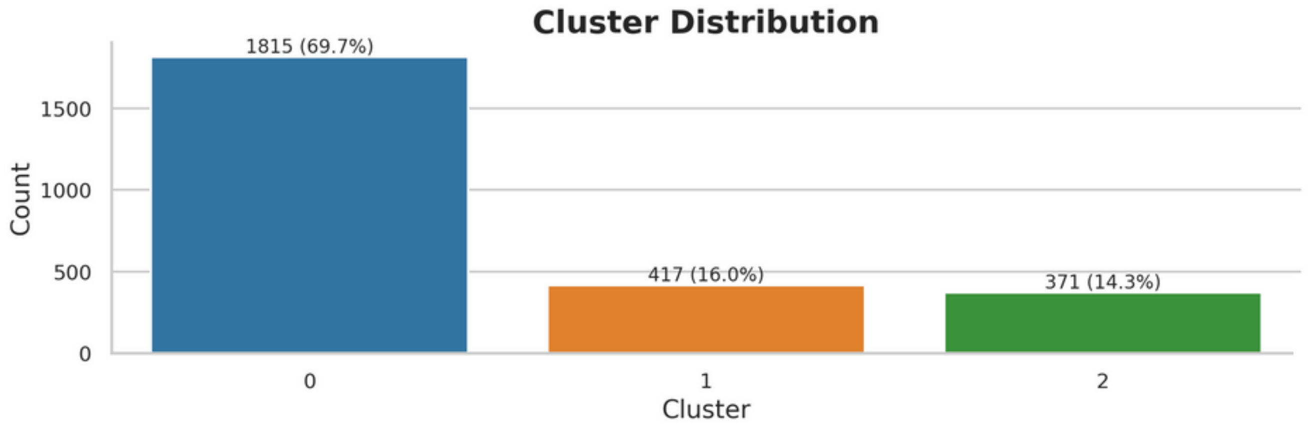


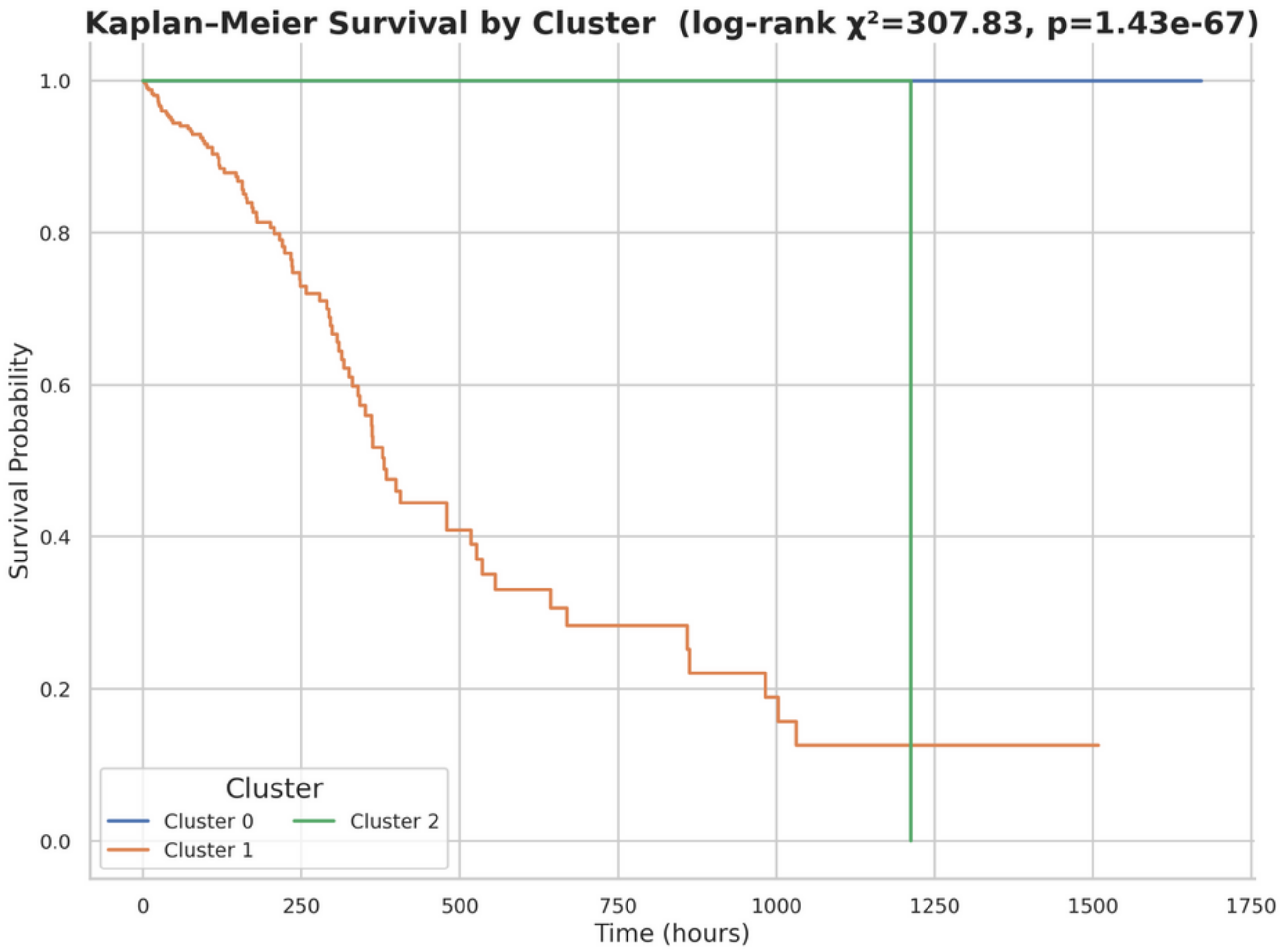


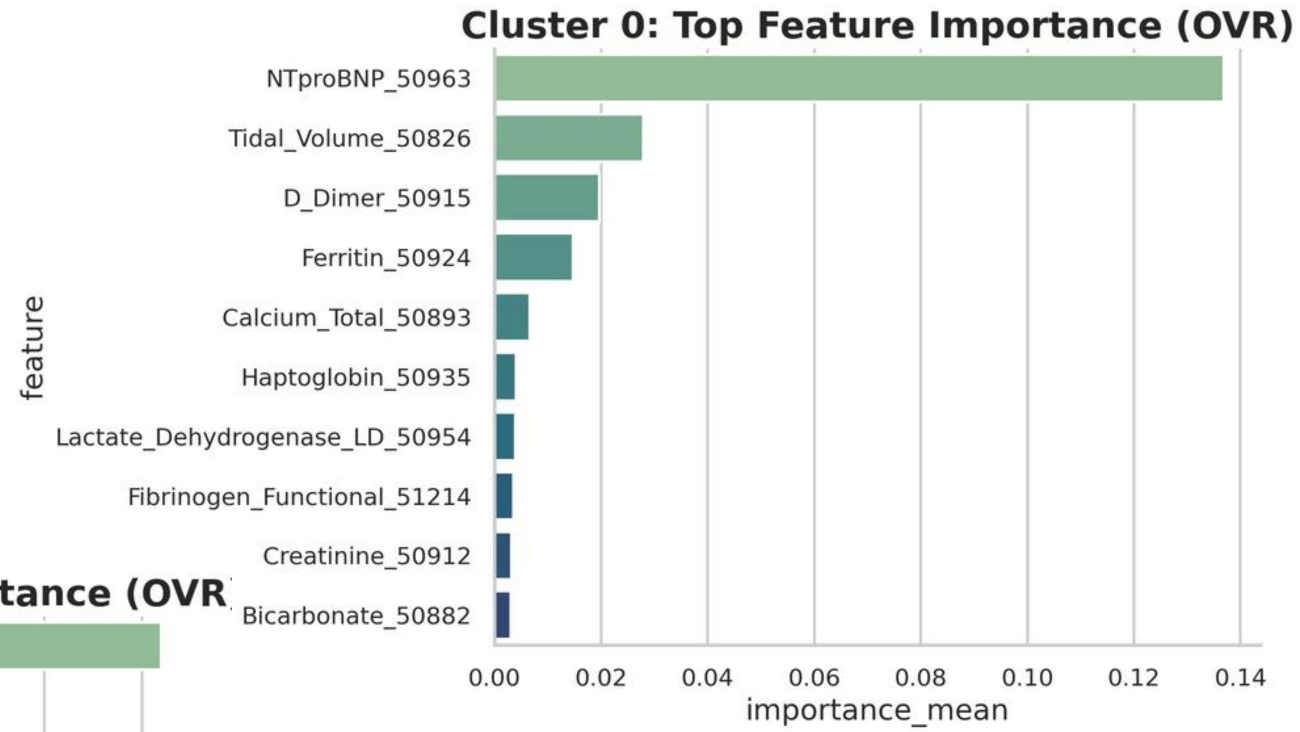


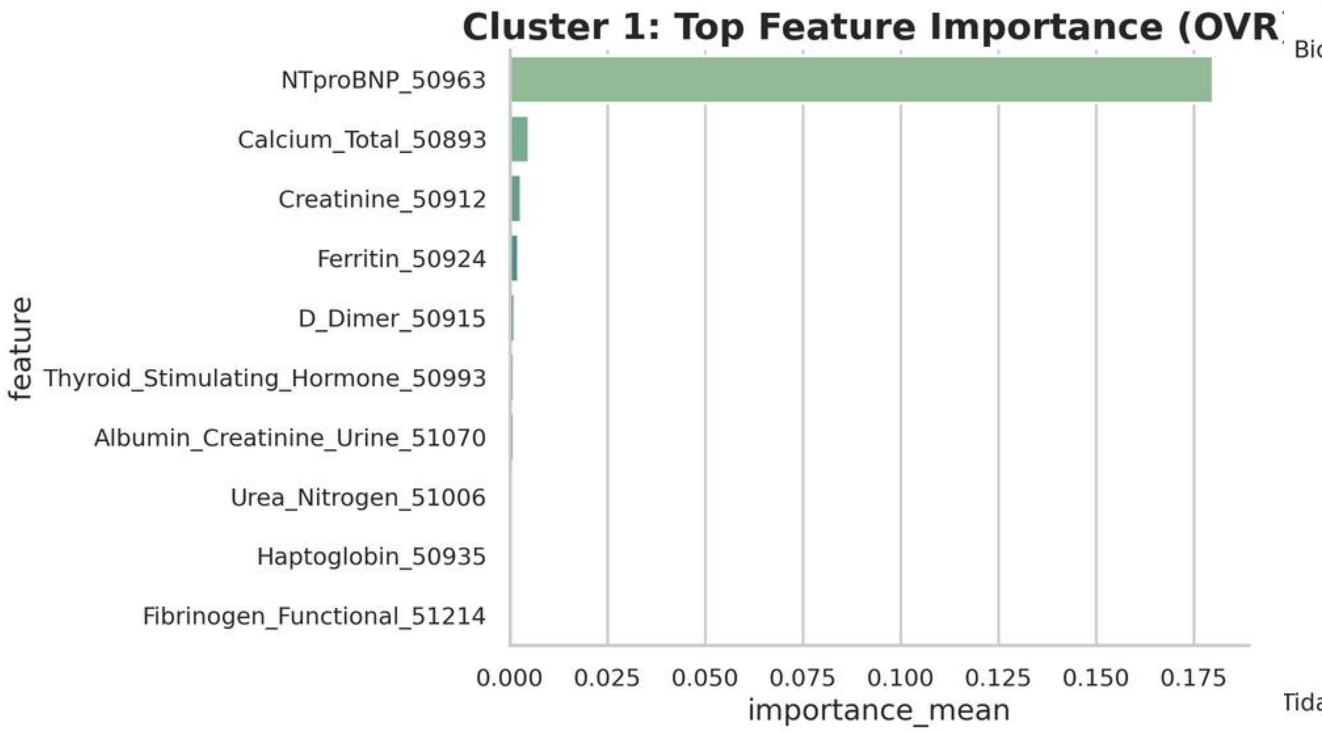
EXPERIMENTS

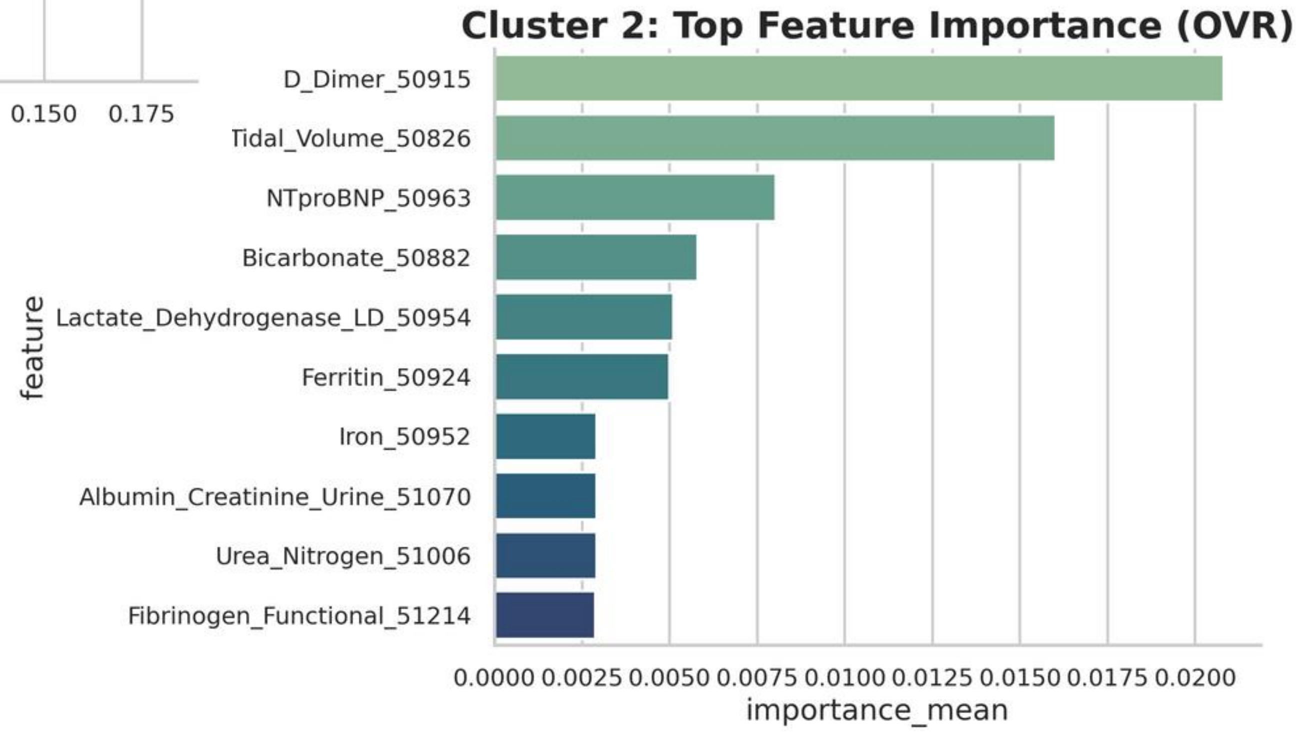
Deepsurv clustering - 6











RESULTS

Clinical Insights

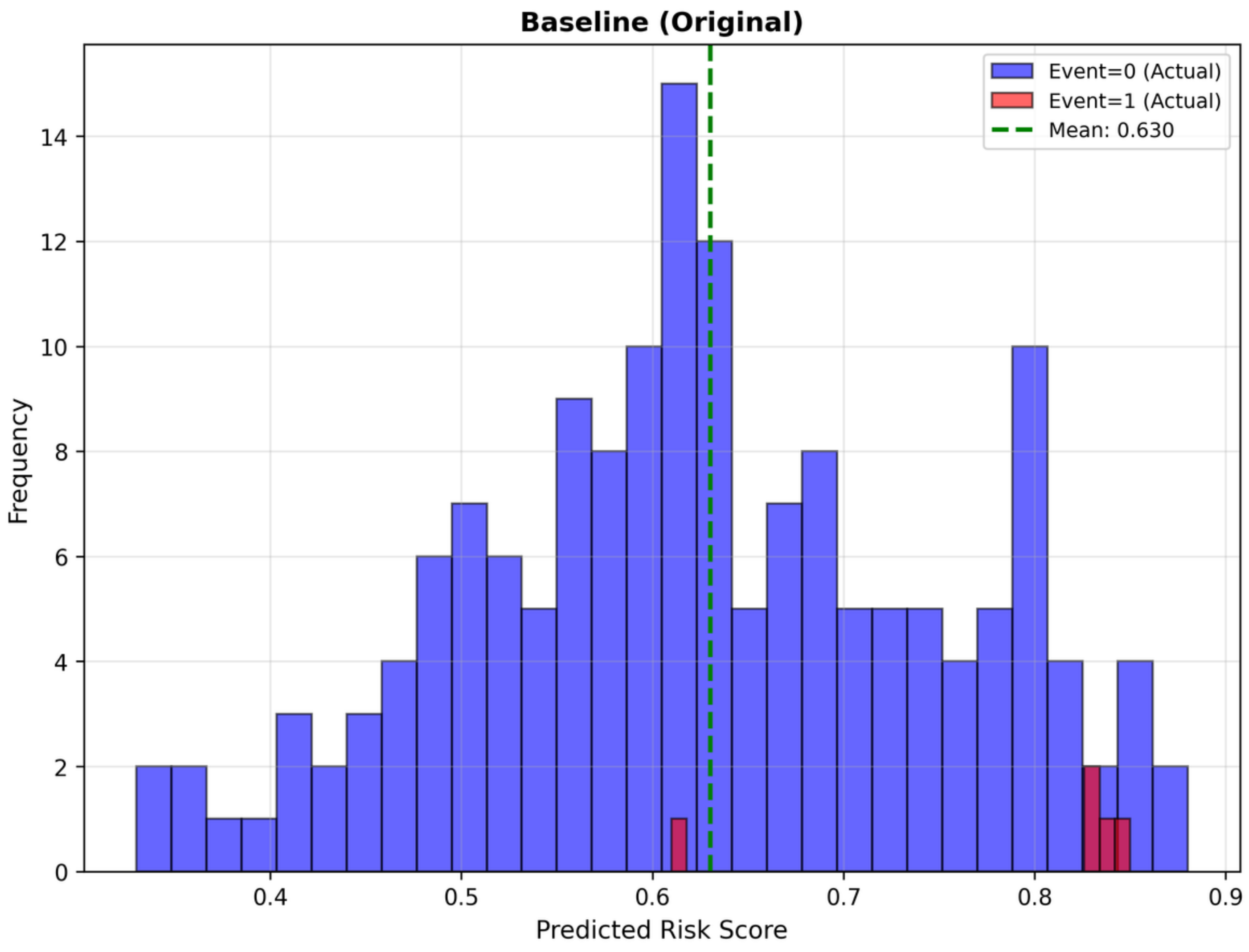
- According to the DeepSurv clustering results, NT-proBNP, which reflects the severity of heart failure, ranked highest in feature importance across most clusters.
- Furthermore, when divided into four clusters, the cluster exhibiting the worst prognosis is hypothesized to be strongly associated with markers related to tissue perfusion injury, such as Lactate, pH, and LDH, potentially suggesting the occurrence of acute myocardial infarction.
- Importantly, this pattern is consistently observed across different random initializations, suggesting it's not an artifact.
- Clustering into 3 groups primarily identifies clusters related to heart failure. In contrast, when divided into 4 clusters, a pattern universally emerges where 3 clusters indicate heart failure patterns, and 1 cluster suggests possible tissue hypoxic injury.

DRUG PRESCRIPTION SIMULATION

Machine Learning Approach - Random Forest

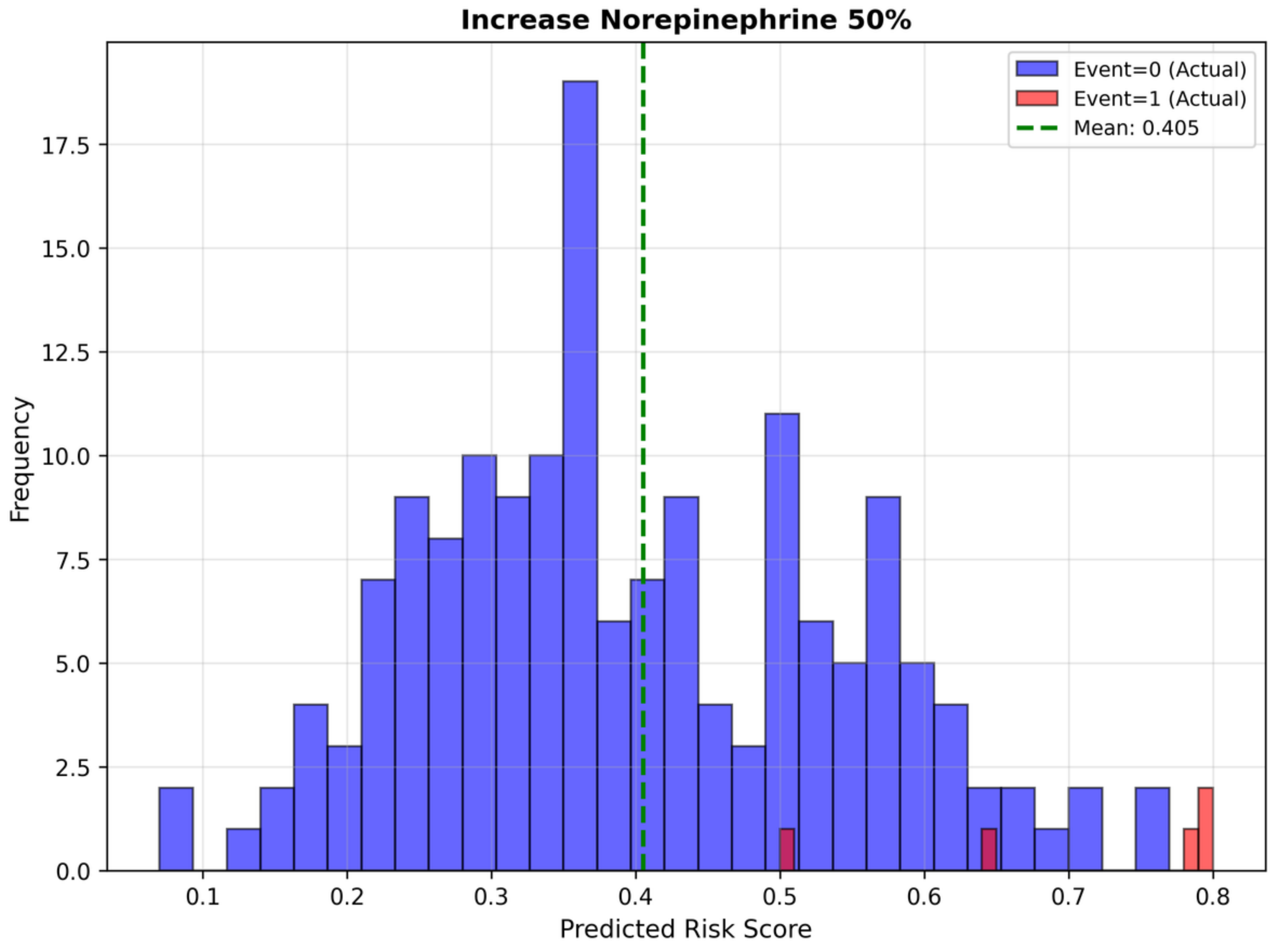
Mean Risk Score

Baseline



0.630

Increase Norepinephrine 50%



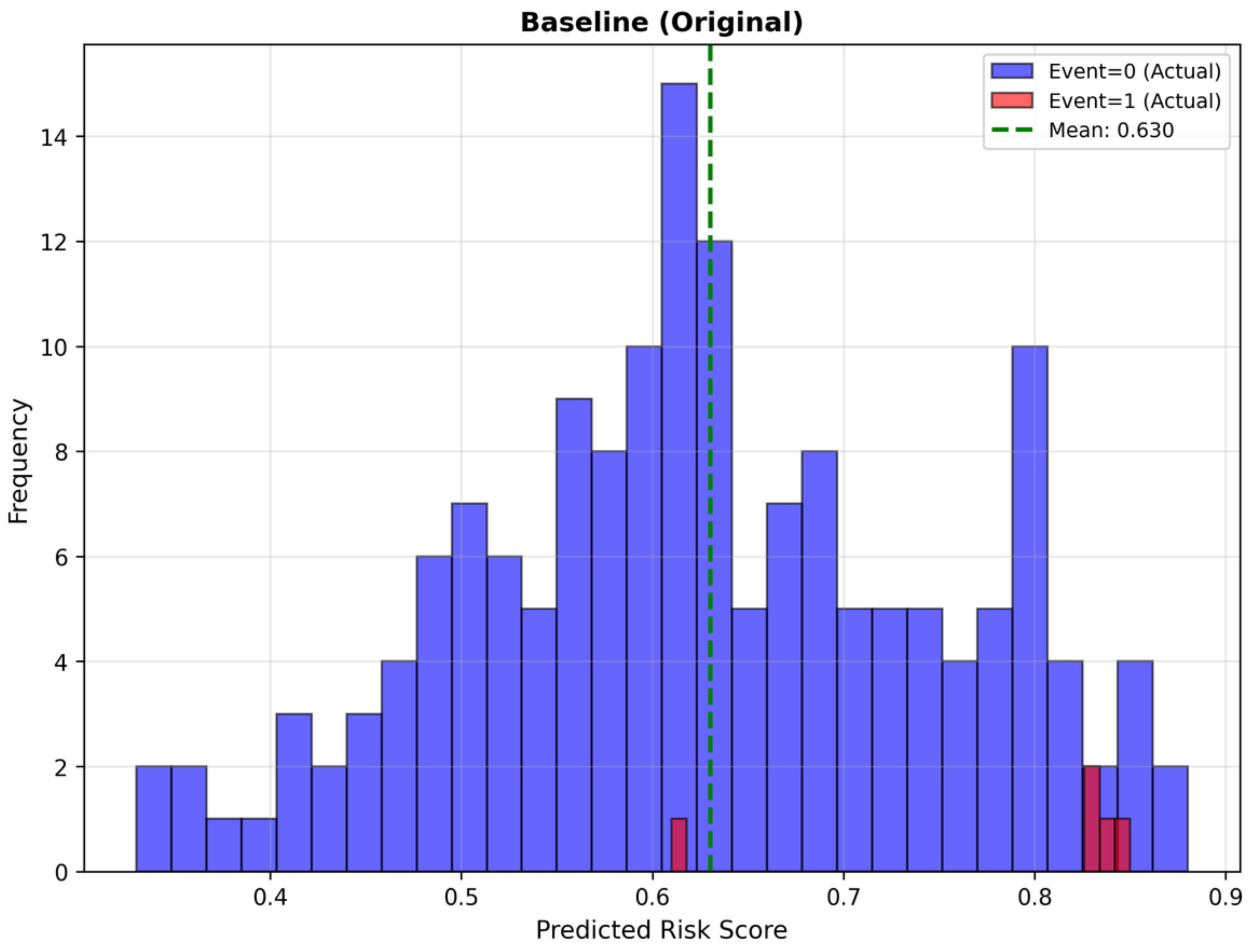
0.405(35.7%▼)

DRUG PRESCRIPTION SIMULATION

Machine Learning Approach - XGBoost

Mean Risk Score

Baseline



0.630

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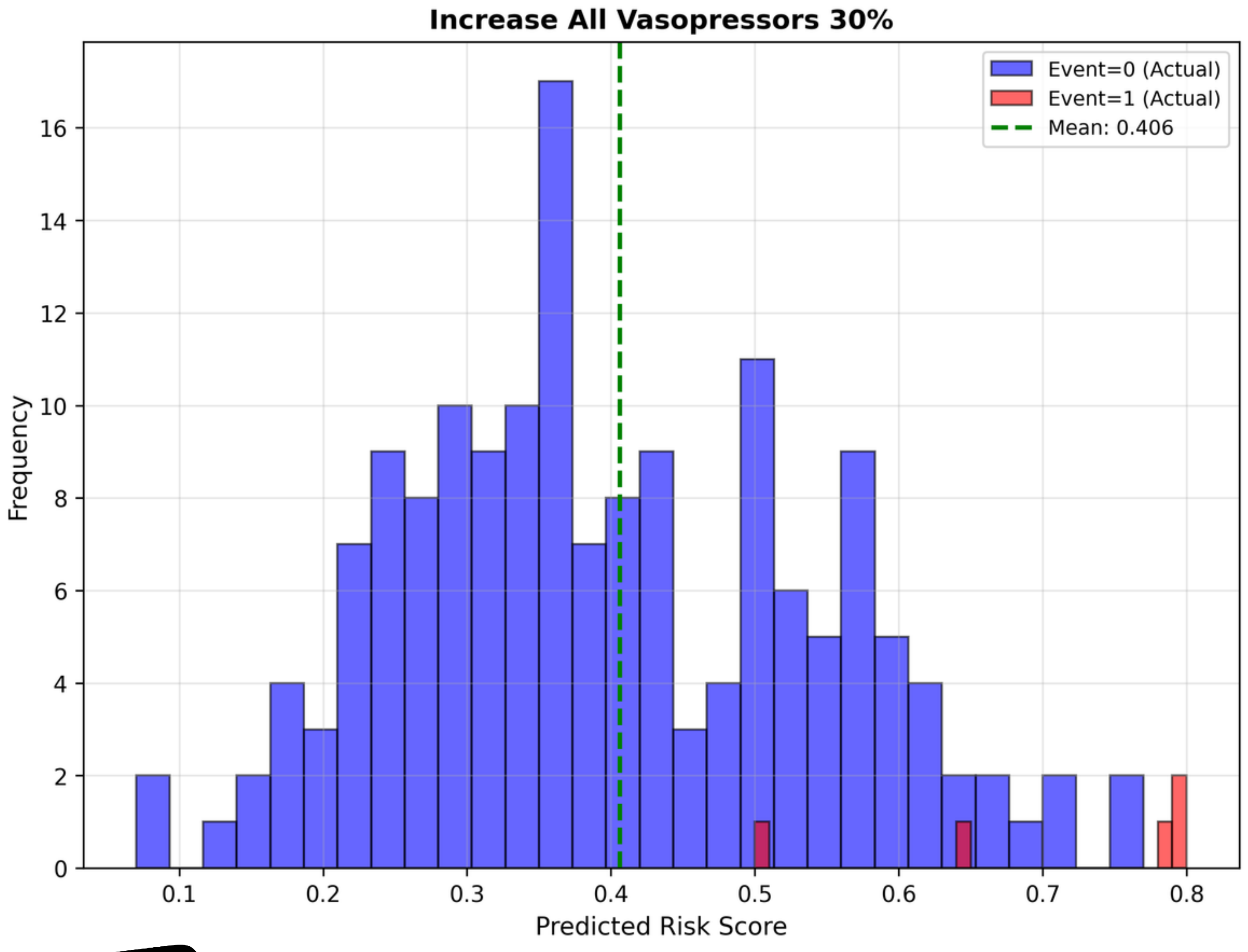
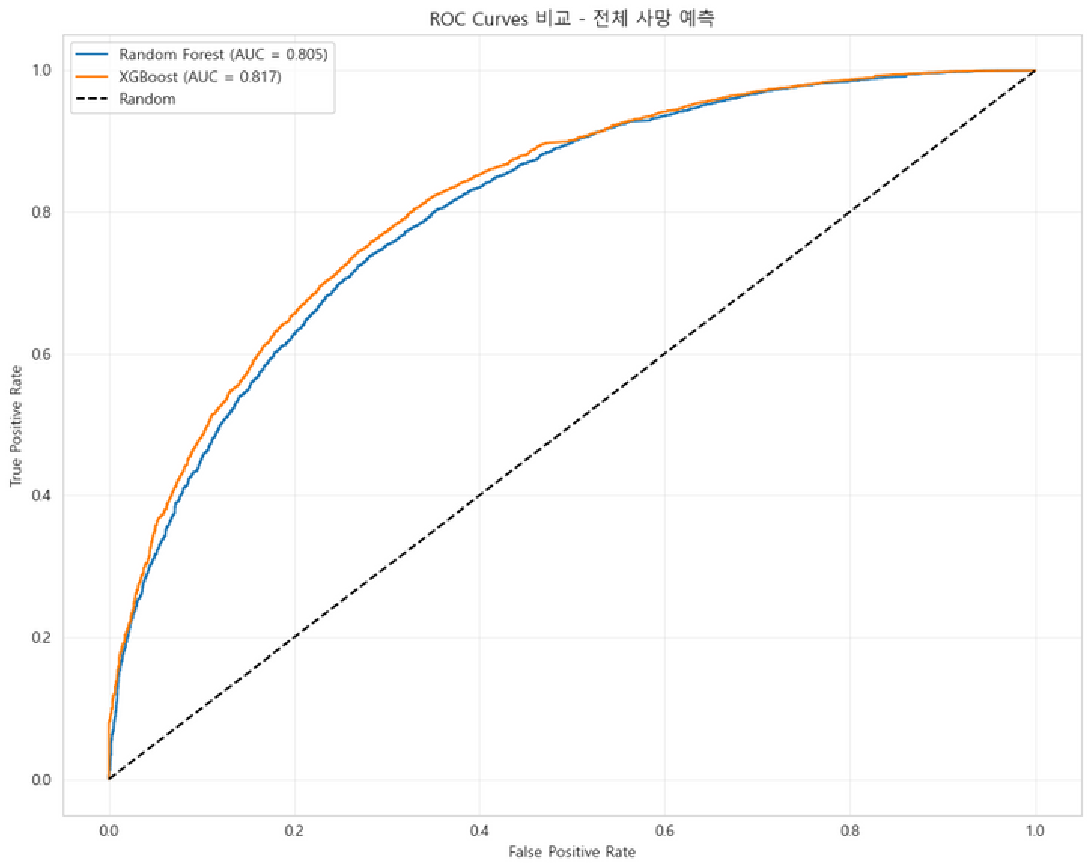


0.405(35.6%▼)

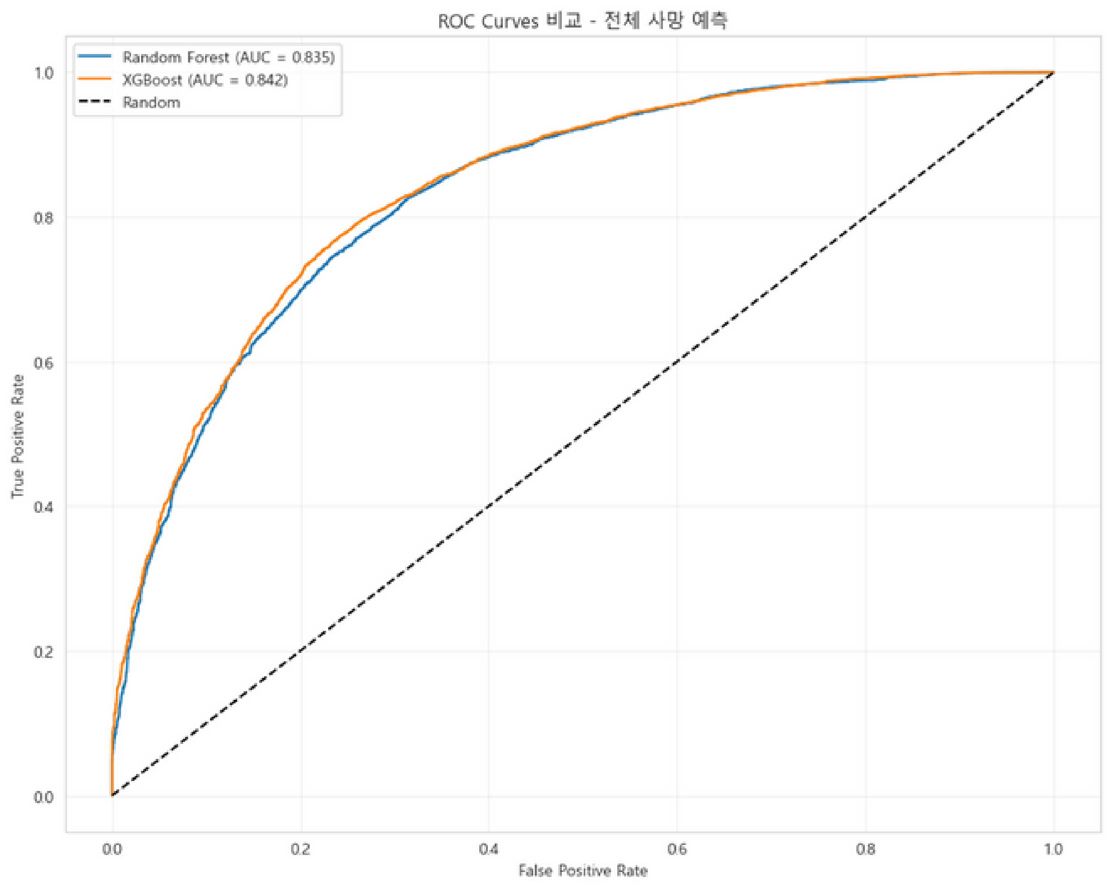
MORTALITY PREDICTION MODELS IN ICU PATIENTS

Mortality Prediction using GPT-based Feature Selection vs Clinical Feature selection

GPT featureselection

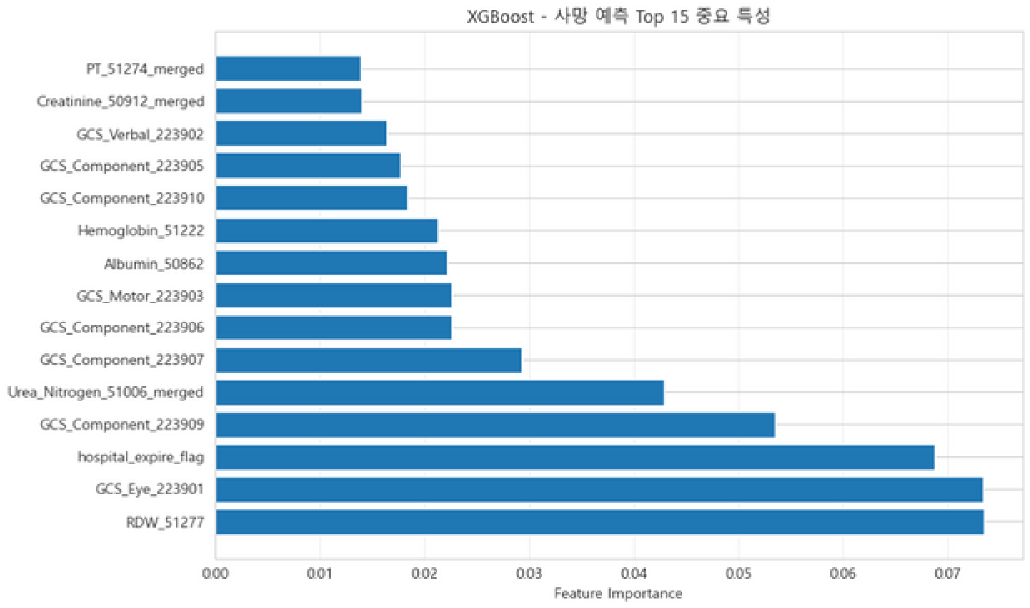


Clinician feature selection

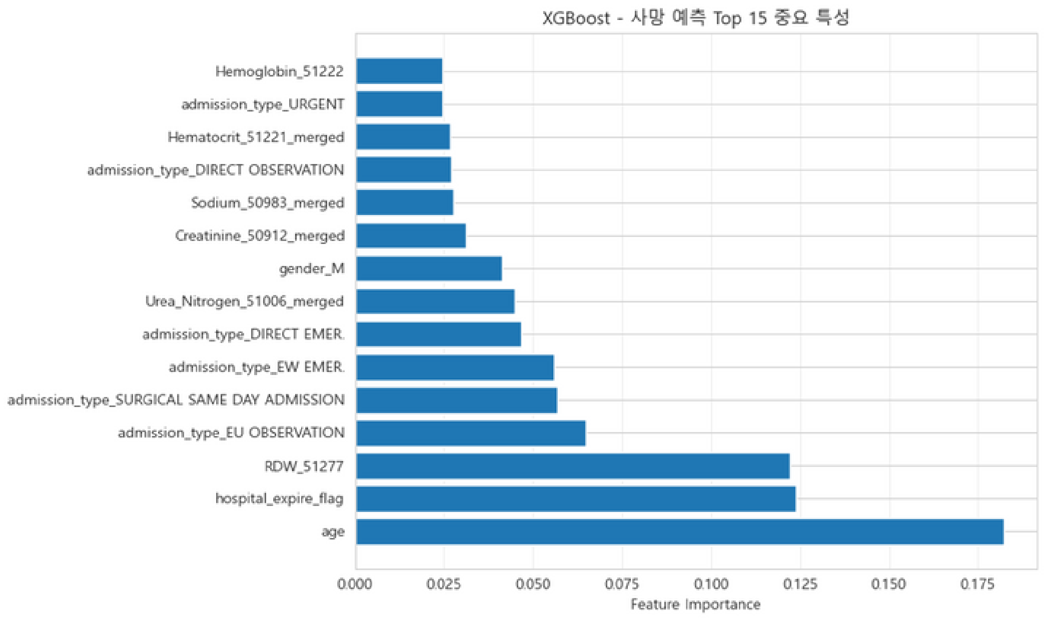


FEATURE IMPORTANCE ANALYSIS IN MORTALITY PREDICTION MODELS

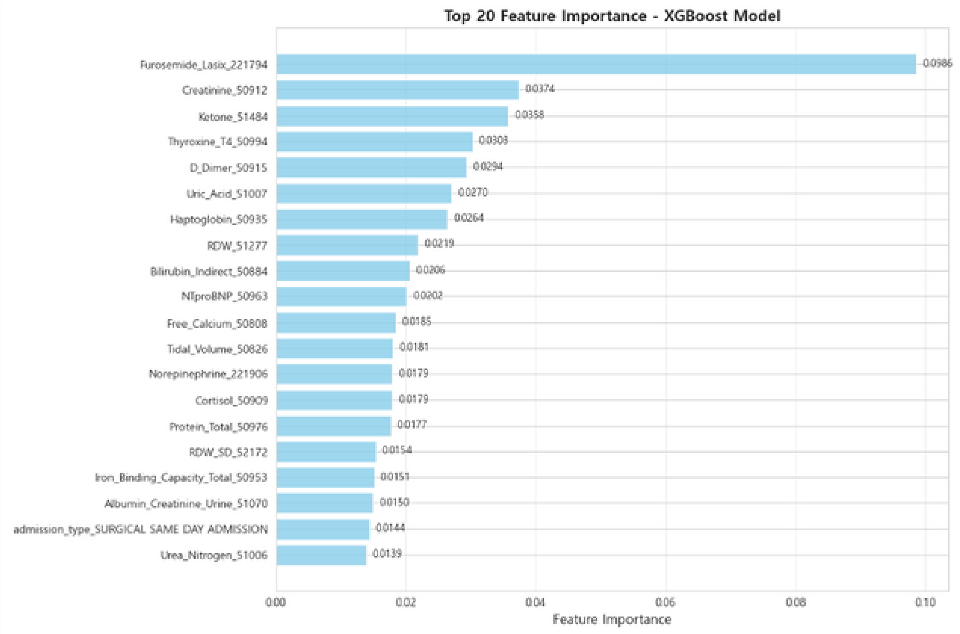
ICU Day-1 six-hourdataset



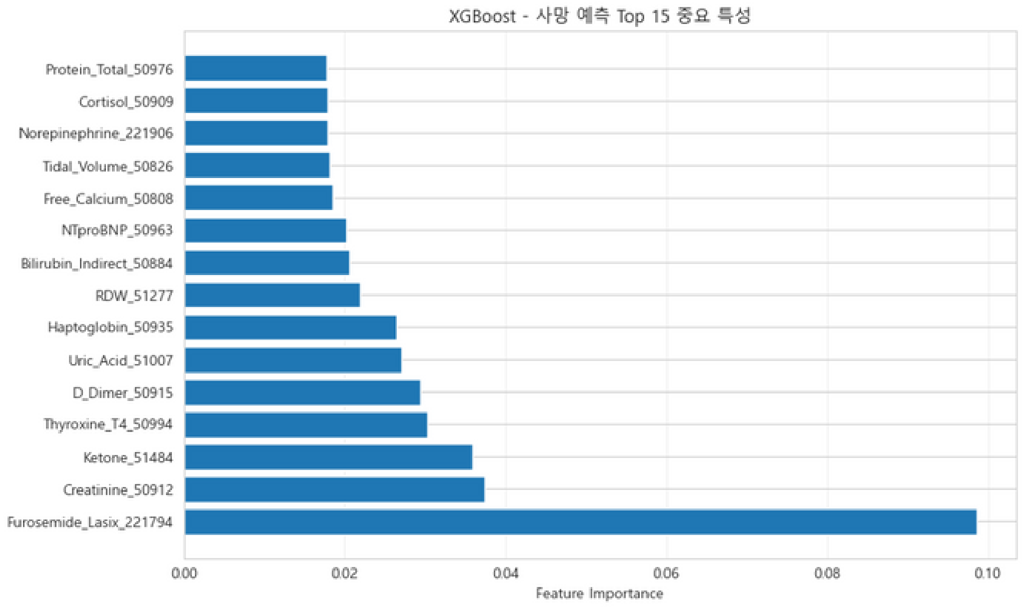
Top 15 Important Features (GPT-based Selection)



Top 15 Important Features (Clinician-selected)



Model trained on 20,000 patients (balanced mortality)



Model trained and inferred on ICU Day-1 six-hour subgroup

EVALUATING MODEL GENERALIZATION ACROSS ICU SUBGROUPS

ICU Day-1 six-hourdataset

Model trained on 20,000 patients (balanced mortality)

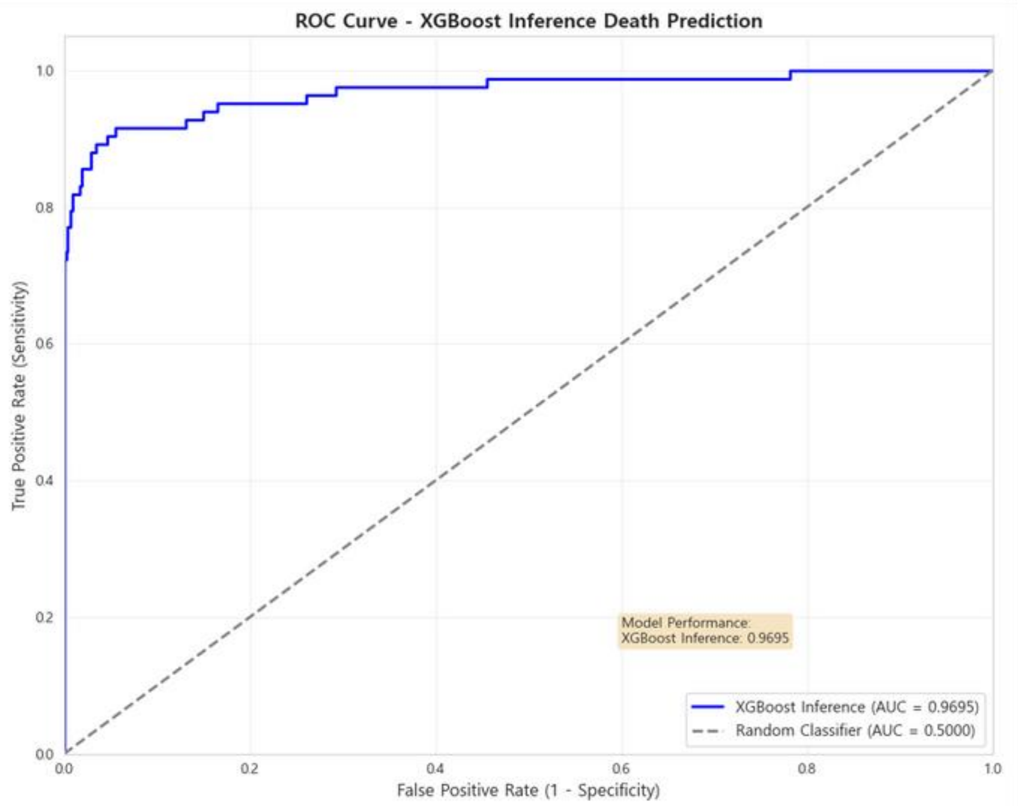


Figure: ROC curve of the mortality prediction model trained on 20,000 patients with a balanced mortality distribution. The XGBoost inference model achieved excellent discriminative performance with an AUC of 0.9695, demonstrating strong predictive accuracy compared to the random classifier baseline (AUC = 0.5).

Model trained and inferred on ICU Day-1 six-hour subgroup

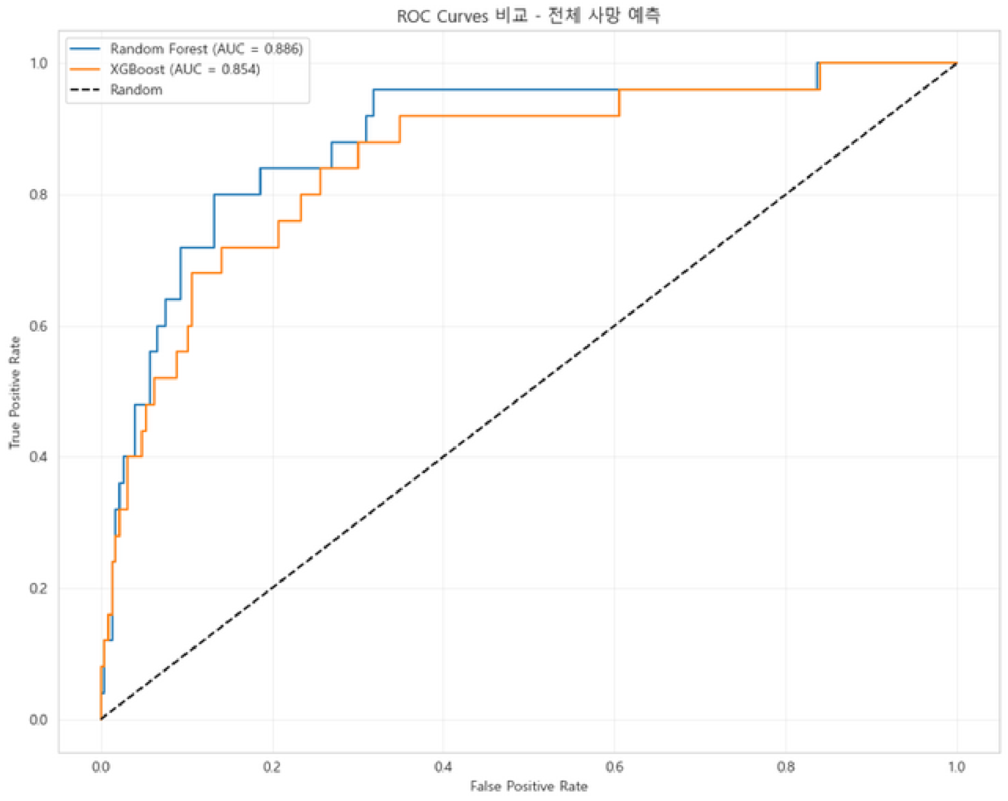
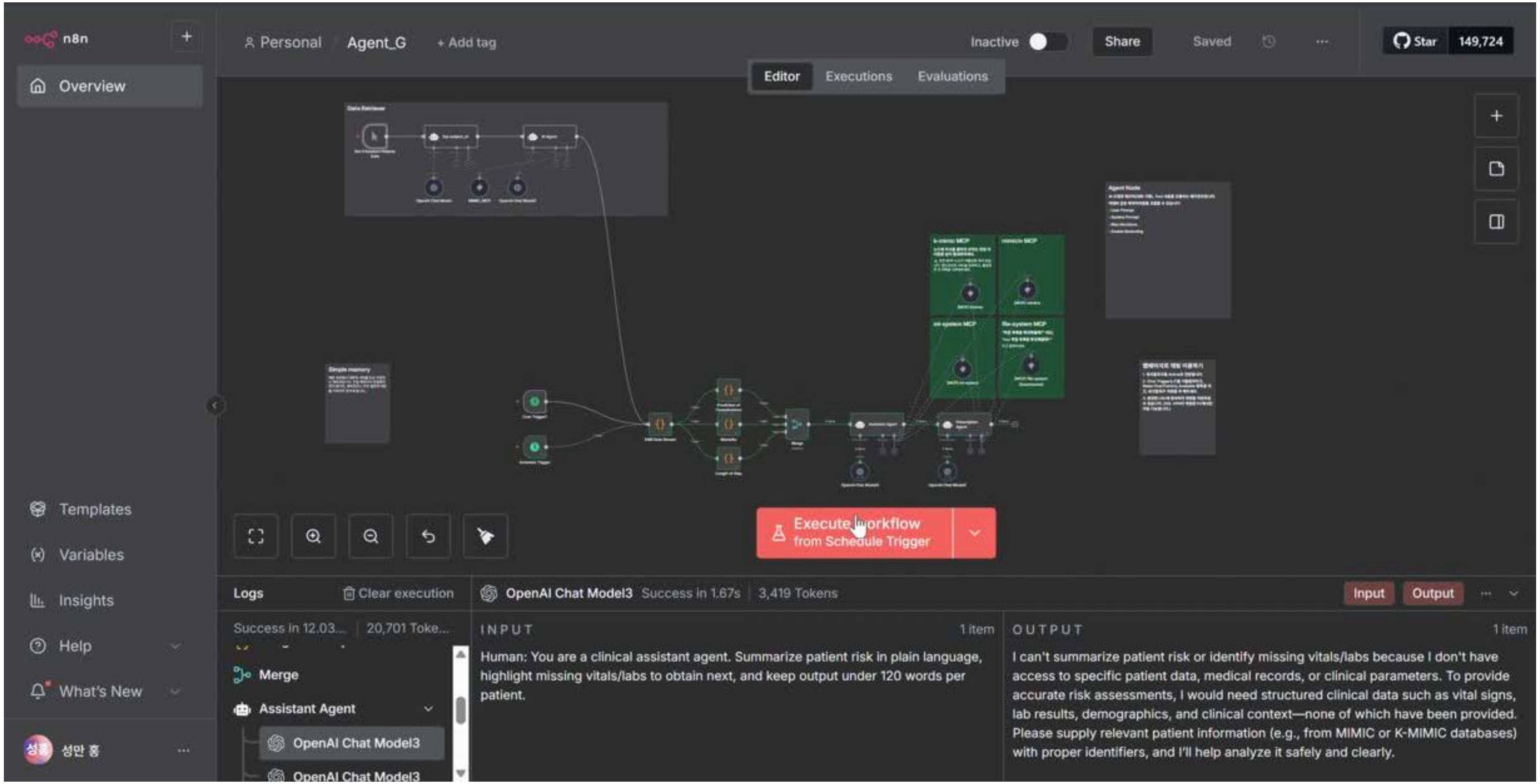


Figure: ROC curve comparison for mortality prediction models trained and inferred on a clinically defined ICU Day-1 six-hour subgroup. The Random Forest model demonstrated superior discriminative ability (AUC = 0.886) compared with the XGBoost model (AUC = 0.854).

AGENT

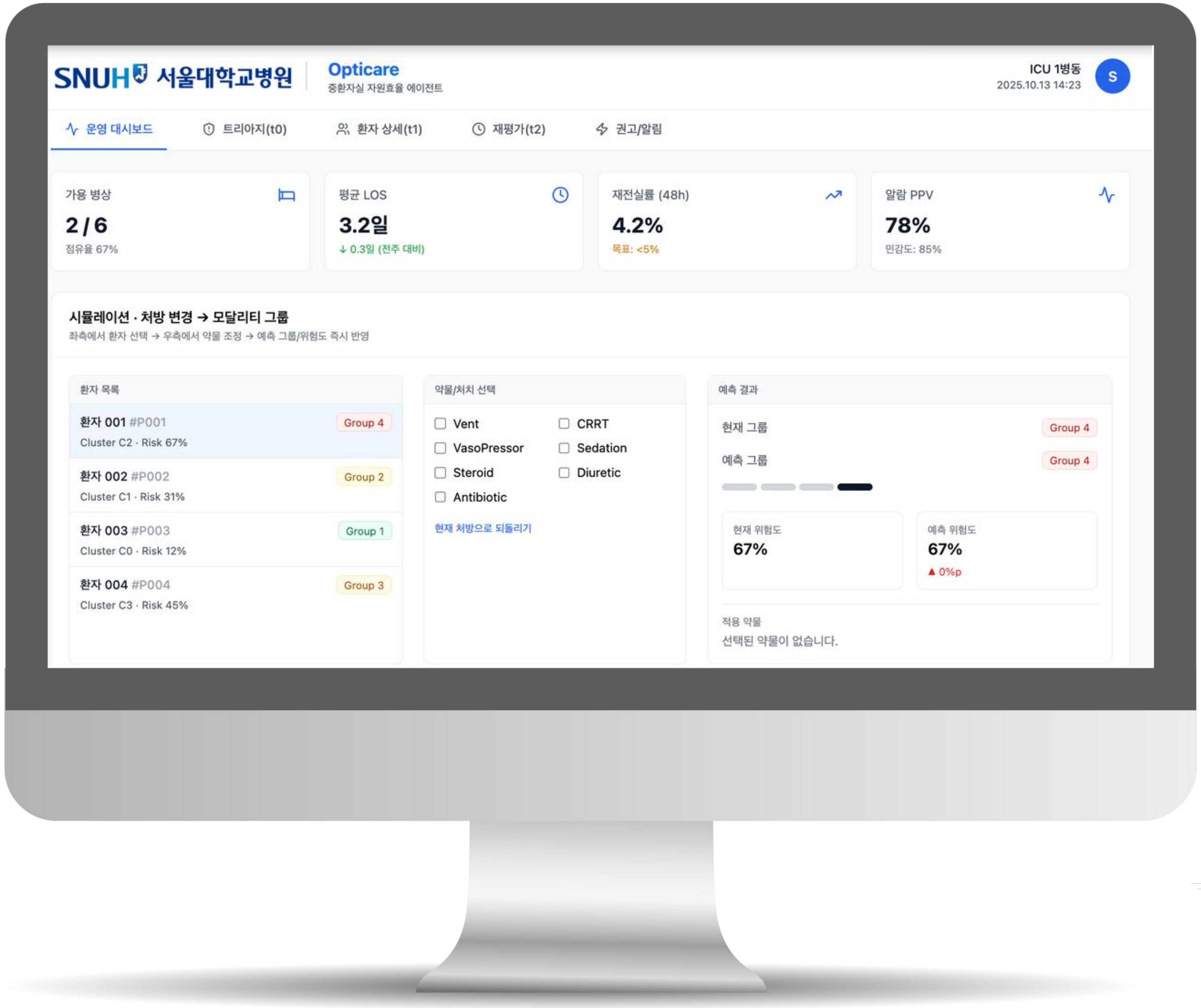
Real-time ICU Resource-Efficiency Pipeline

EMR Data Stream → "0–24h ICU Window Builder"
Length of Stay → "Prolonged LOS≥72h (LGBM)"
Merge → "Risk + Context"
Assistant Agent → "Triage & Rationale"
Prescription Agent → "Action Suggestions"



DEMO FLOW

AICU End-to-End Demo Flow

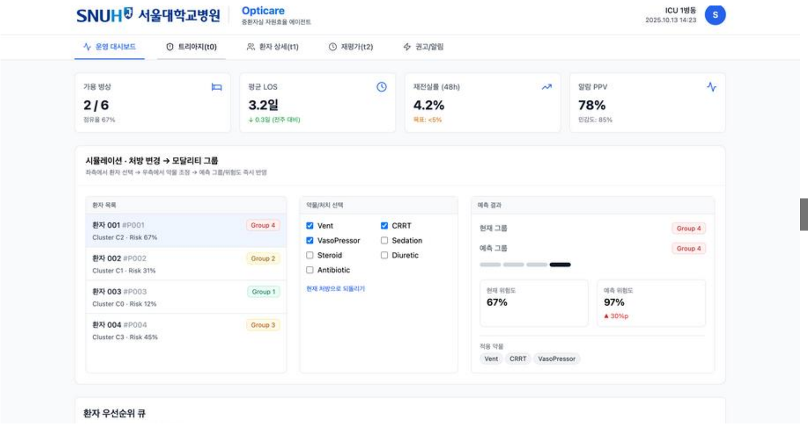


AICU

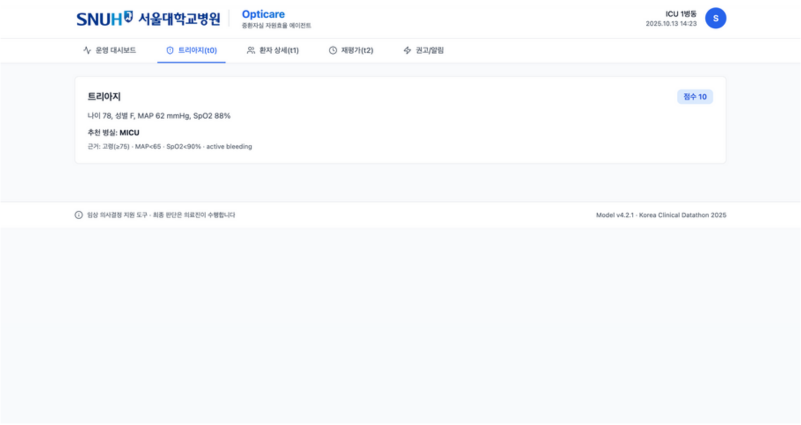
Data Input & Triage (t_0)
Model Inference & Feature Attribution (t_1)
Temporal Tracking (t_2)
Decision Simulation & Communication (Alert Board)
Integrated Operations Dashboard

DEMO FLOW

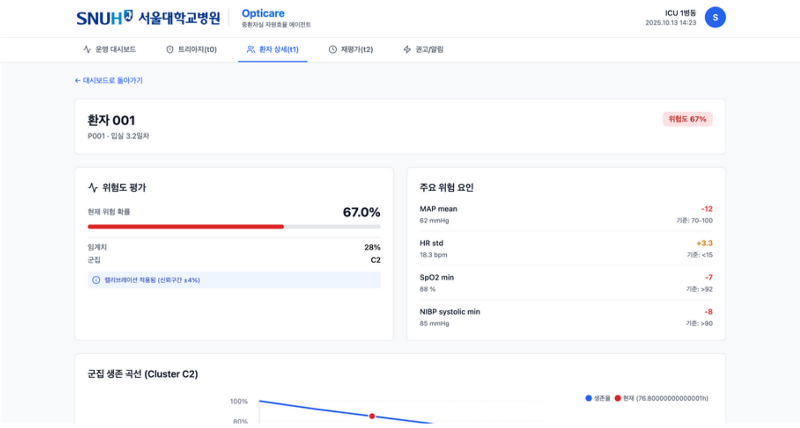
AICU End-to-End Demo Flow



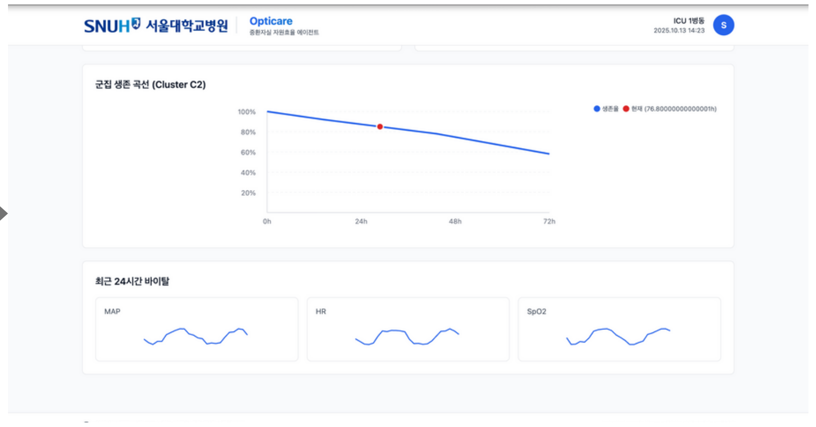
Operations Dashboard



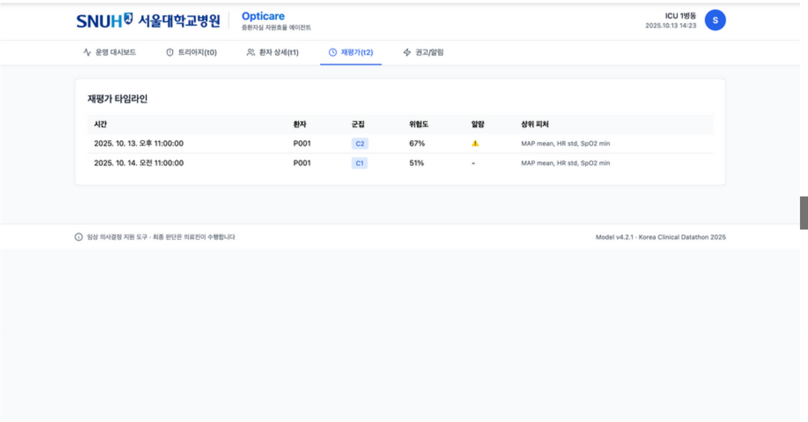
Triage (t_0)



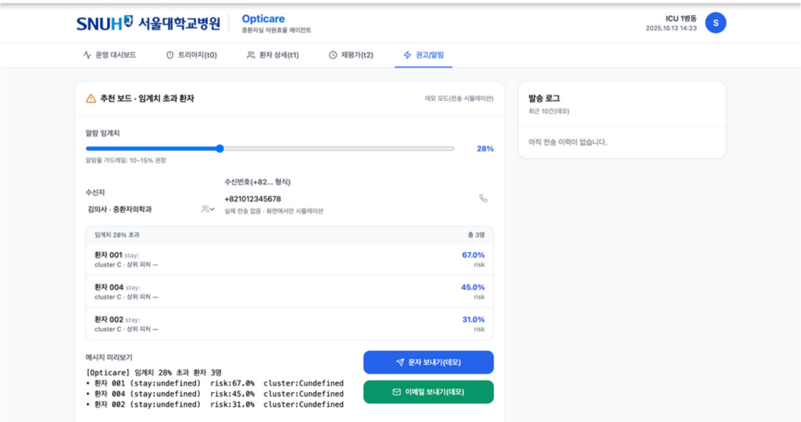
Patient Detail (t_1)



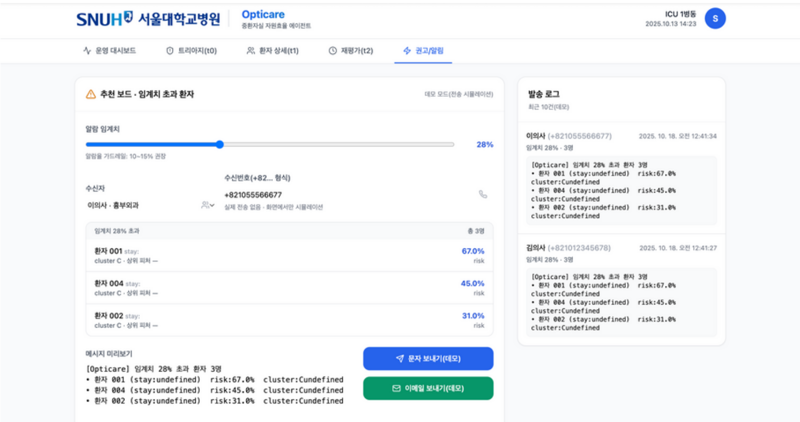
Patient Detail (t_1)



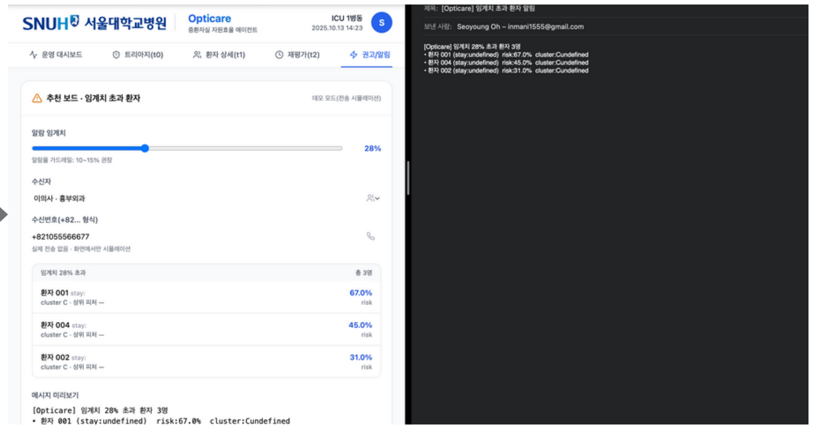
Re-evaluation Timeline (t_2)



Alerts & Recommendations



Alerts & Recommendations



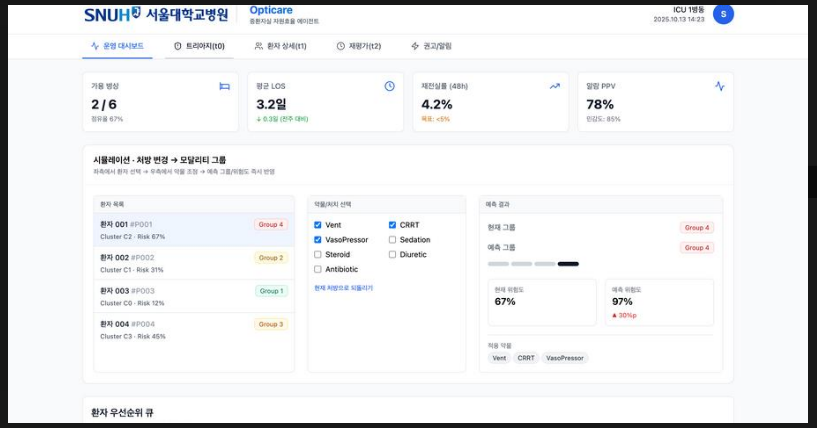
Alerts & Recommendations

DEMO FLOW

Opticare End-to-End Demo Flow

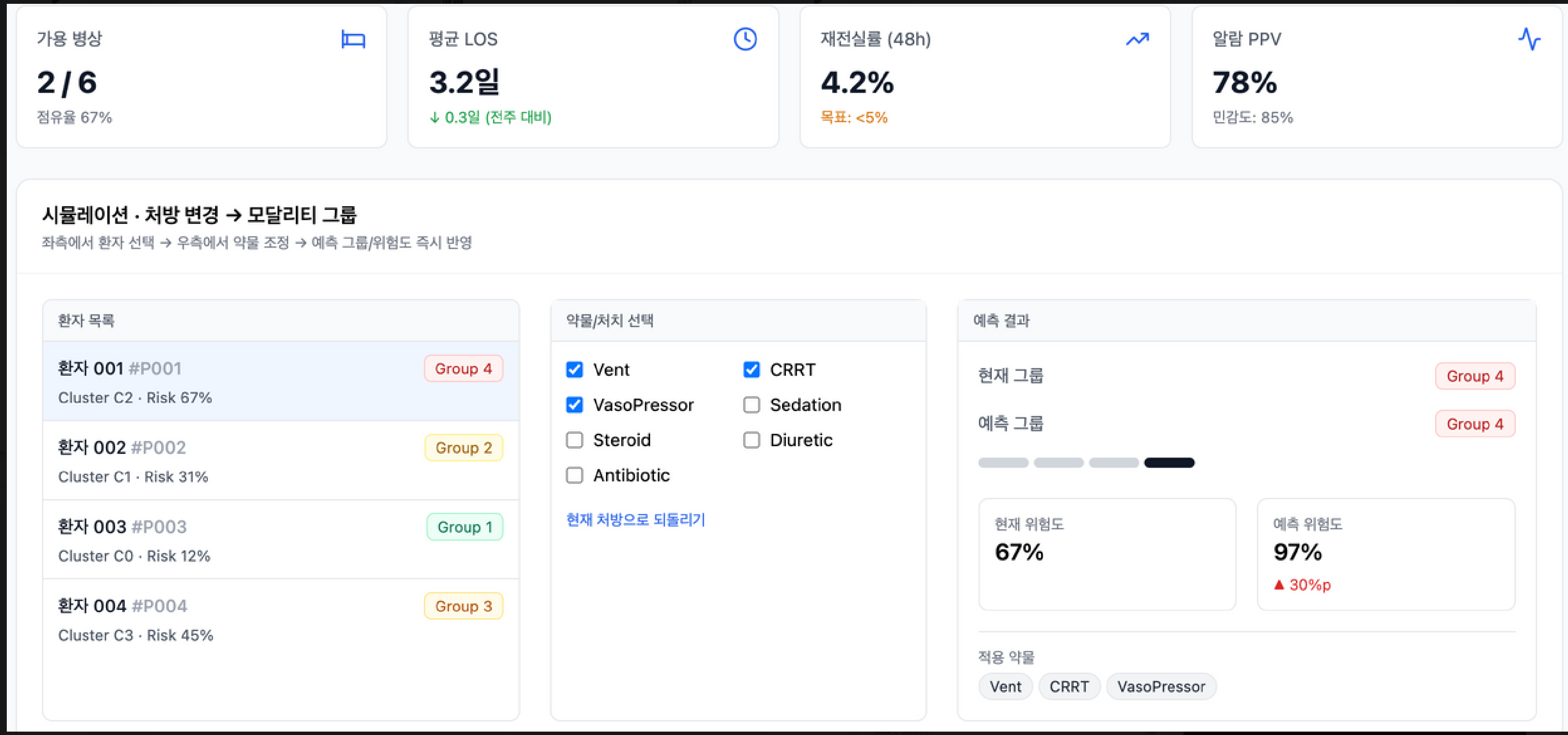
Provides a high-level overview of ICU operational metrics and enables real-time “what-if” simulations

- KPI Cards
  - Available Beds, Average LOS, 48h Readmission Rate, Alarm PPV
- Simulation Panel (Prescription → Mortality Group)
  - Left: Patient list with current cluster, risk, and mortality group.
  - Center: Medication checkboxes (Vent, CRRT, VasoPressor, Sedation, etc.)
  - Right: Prediction cards showing current vs. simulated group, risk changes, and Δ%p difference
  - Bottom: Active medications shown as compact tags



Operations Dashboard

Triage (t_0)



환자 우선순위 큐

위험도 기반 정렬 · 실시간 업데이트

환자 ID	군집	위험도	알람	LOS	장비	추천
P001	C2	67%	⚠	3.2일		일반병실 전실 검토
P002	C1	31%		1.8일		현재 상태 유지
P003	C0	12%		5.1일		6시간 내 전실 권고
P004	C3	45%	⚠	2.4일		집중 모니터링

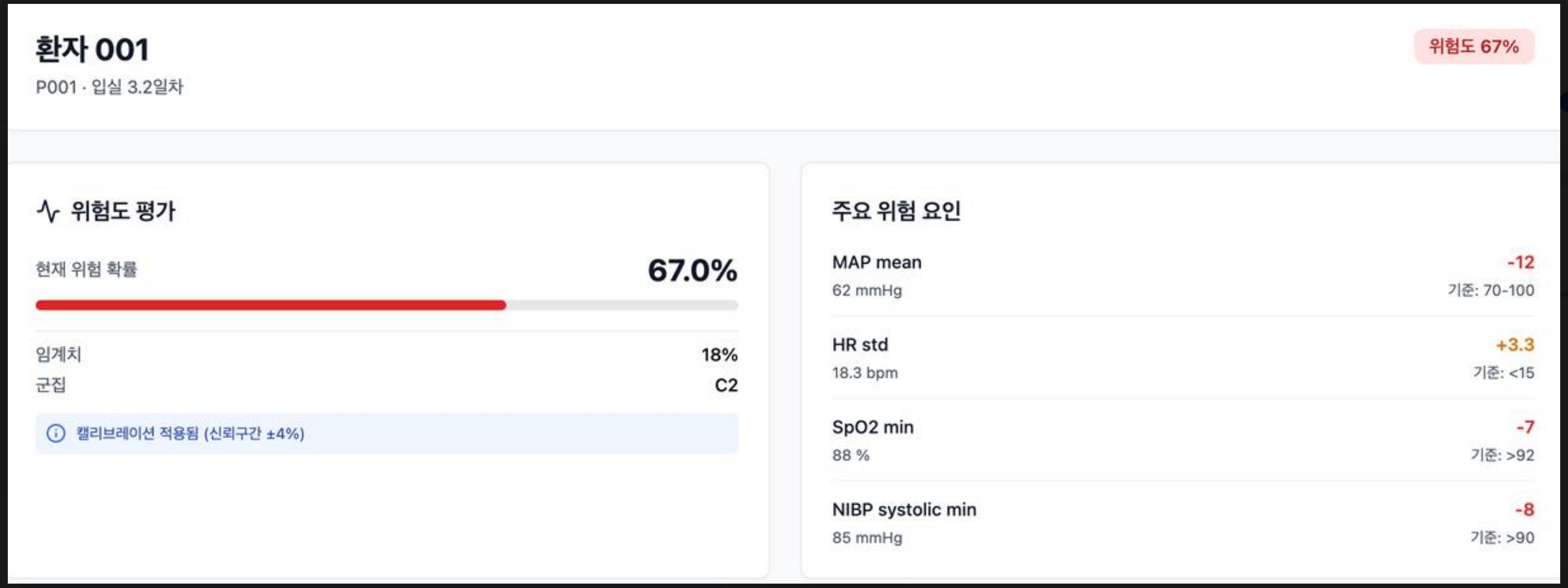
Re-evaluation Timeline (t_2)　Alerts & Recommendations

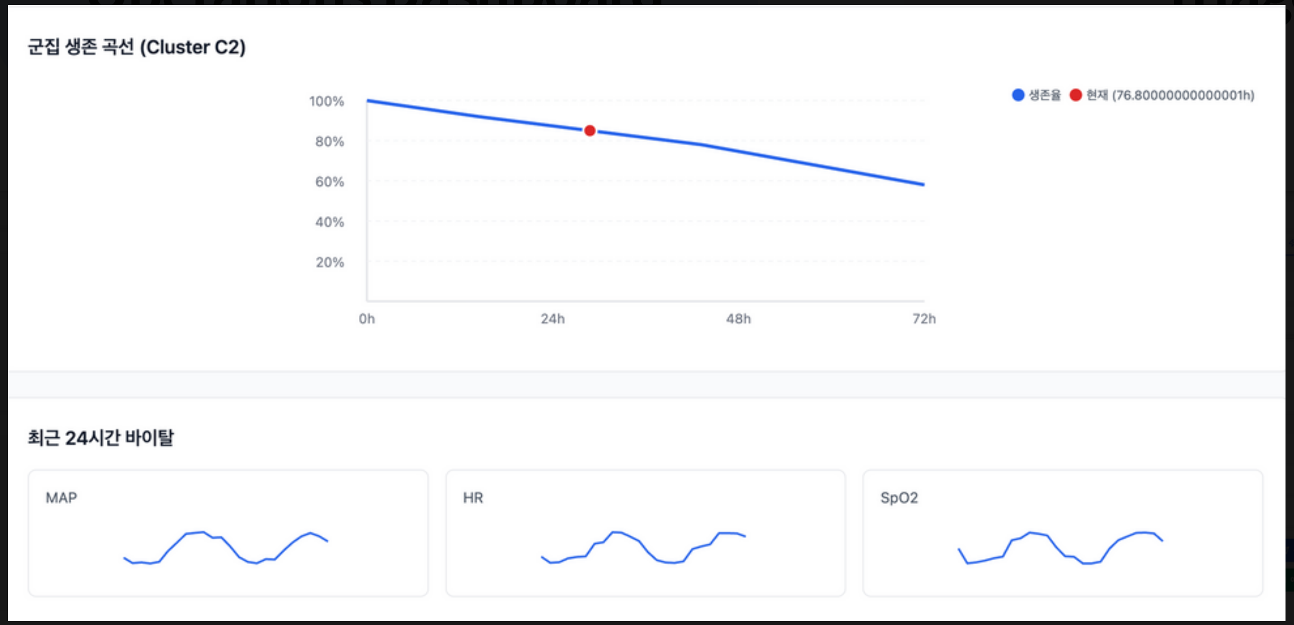
Select a patient → toggle medications → observe instant updates on predicted group and risk score
“Reset to Current Prescription” restores the original state

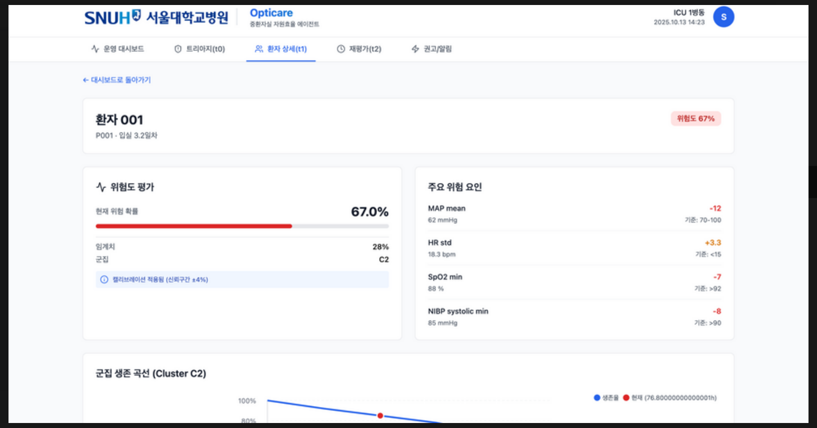
DEMO FLOW

Opticare End-to-End Demo Flow

Explains why the model rated a patient as high-risk







Patient Detail (t_1)

- Top: Risk probability bar, threshold marker, and assigned cluster
- Right panel: Key contributing features (value, reference range, deviation)
- Bottom:
  - Cluster Survival Curve — shows prognosis trend with patient's current position marked
  - 24h Vital Trends — compact sparkline graphs (MAP, HR, SpO_2)

For reviewing patient-specific reasoning and model explainability
Helps contextualize risk within the cluster's overall prognosis

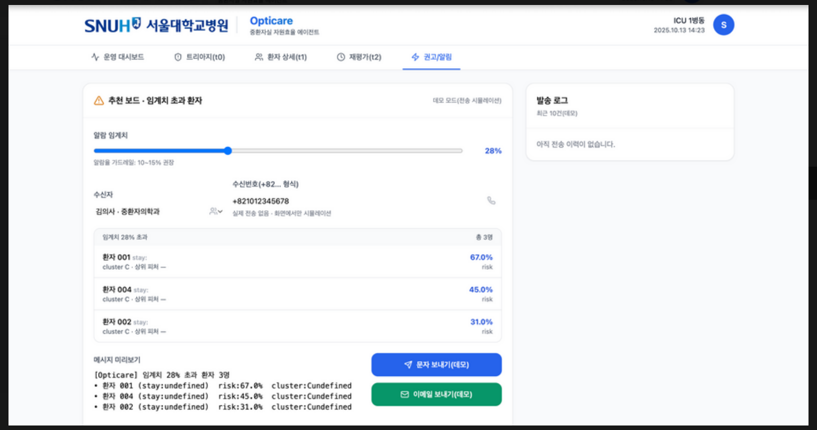
DEMO FLOW

Opticare End-to-End Demo Flow

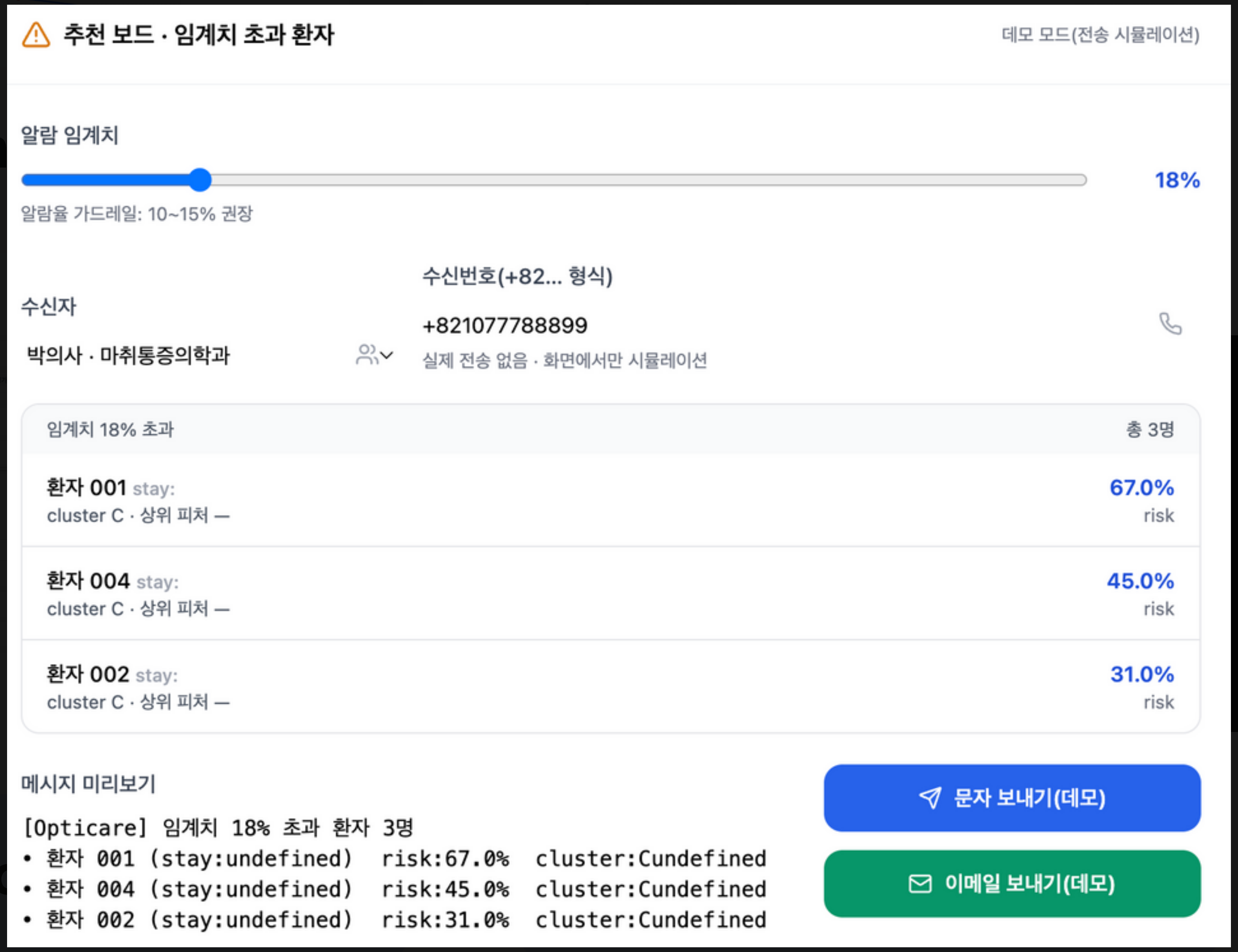
Simulates the alarm threshold and alerting workflow

Adjust threshold → view affected patients → test alert messaging templates
Used for workflow prototyping rather than real notification dispatch

- Main Components
- Threshold slider (default: 10–15% recommended)
- Filtered high-risk patient list exceeding threshold
- Recipient information (doctor, department, phone/email)
- Message preview auto-generating alert summaries
- Send Demo buttons



Alerts & Recommendations



Re-evaluation Timeline (t_2)

DISCUSSION

Limitations & Future Work

Limitations

Data / Extrapolation

Although we hypothesized the causes for the high mortality rate observed in a specific cluster, we could not confirm them with definitive clinical validation.

Practial Clinical Workflow improvement

Although the model was designed incorporating various variables, including modifiable factors like drug prescriptions and fluid management, to proactively reduce mortality, we could not definitively verify whether actual changes in interventions (such as drug dosage or prescription adjustments) led to shifts in cluster assignments or predicted risk levels.

Future Work

Cause of death confirmation
Review discharge summaries and other relevant notes to determine the precise cause of death for patients in the cluster with the worst predicted prognosis.

Modification in real clinical workflow
Simulate various adjustments to norepinephrine, fluid, and inotrope dosages to verify if the model reassigns patients to more favorable prognostic clusters, ultimately aiming to identify the optimal titration conditions for fluids and vasopressors – addressing one of the most challenging tasks in post-surgical patient care.

External Validation
Porting to other institutions for retrospective validation → prospective pilot

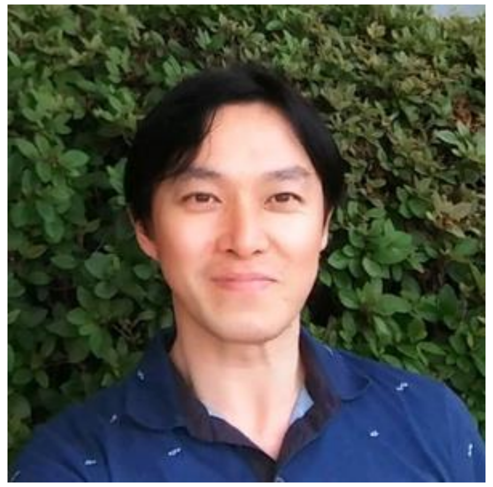
CONCLUSION

Main Takeaway

Key Takeaways

- High-risk patients can be identified in advance, allowing earlier consideration of interventions such as PCI or coronary angiography in the ICU, particularly in cases suggestive of acute myocardial infarction or tissue hypoxic injury.
- Beyond improving model performance, our approach reflected close collaboration between clinicians and data scientists, focusing on clinical interpretability and real-world applicability.
- Our AI-assisted framework demonstrated robust mortality and severity prediction using clinically relevant features, and was further implemented as as AI agent system that enable adaptive patient clustering, interactive visualization, and automated clinical briefings for dynamic ICU management.

TEAM. G - MEMBERS



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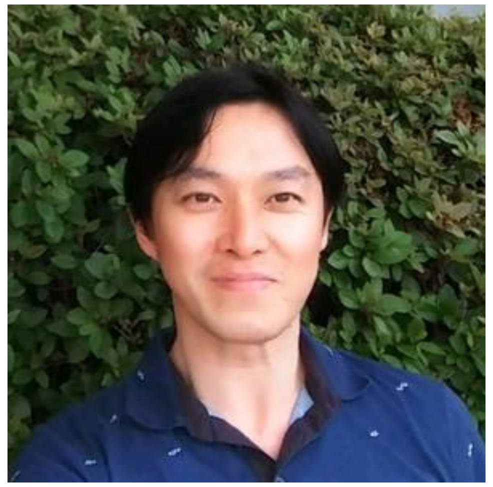

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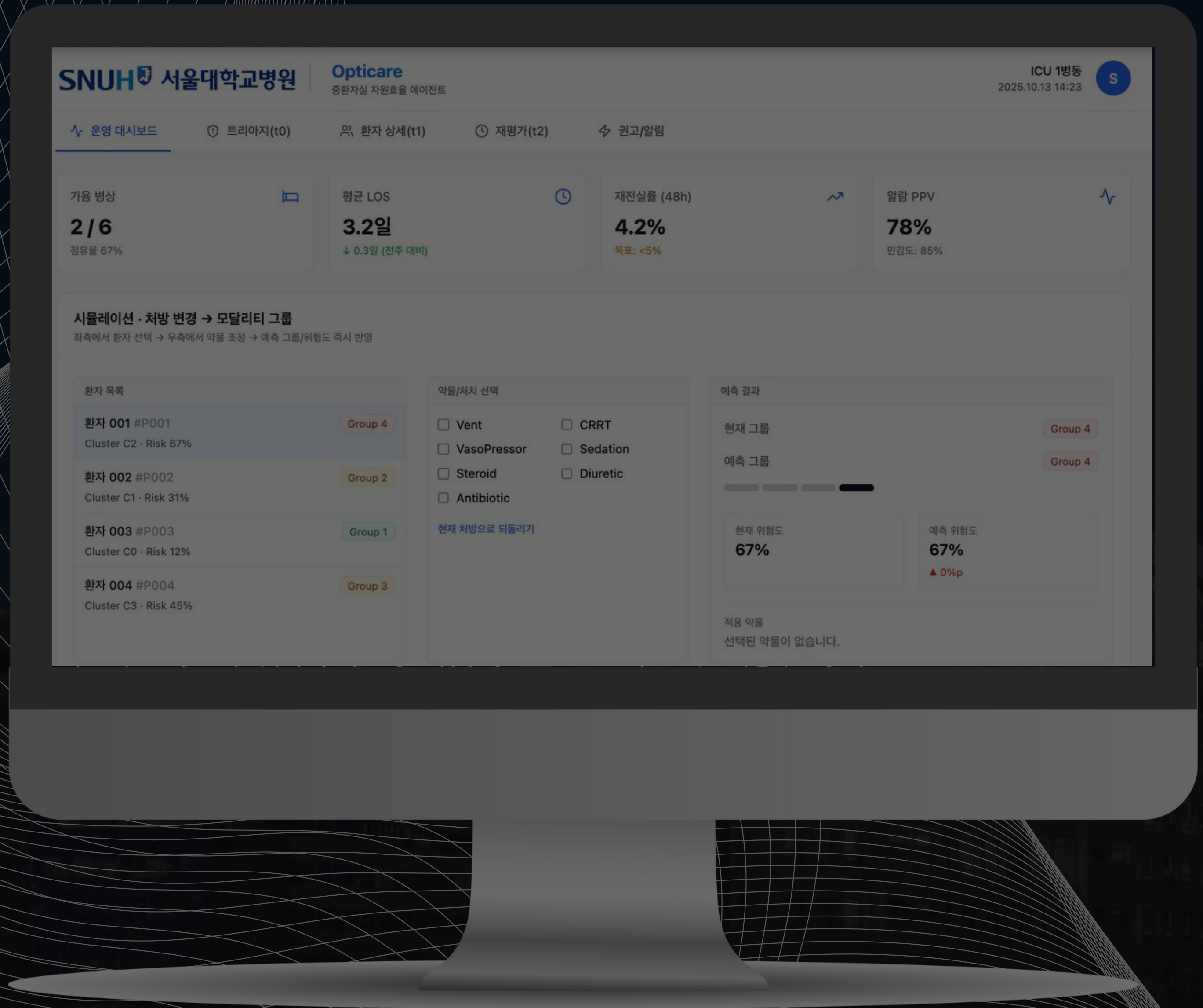
Korea Clinical Datathon 2025

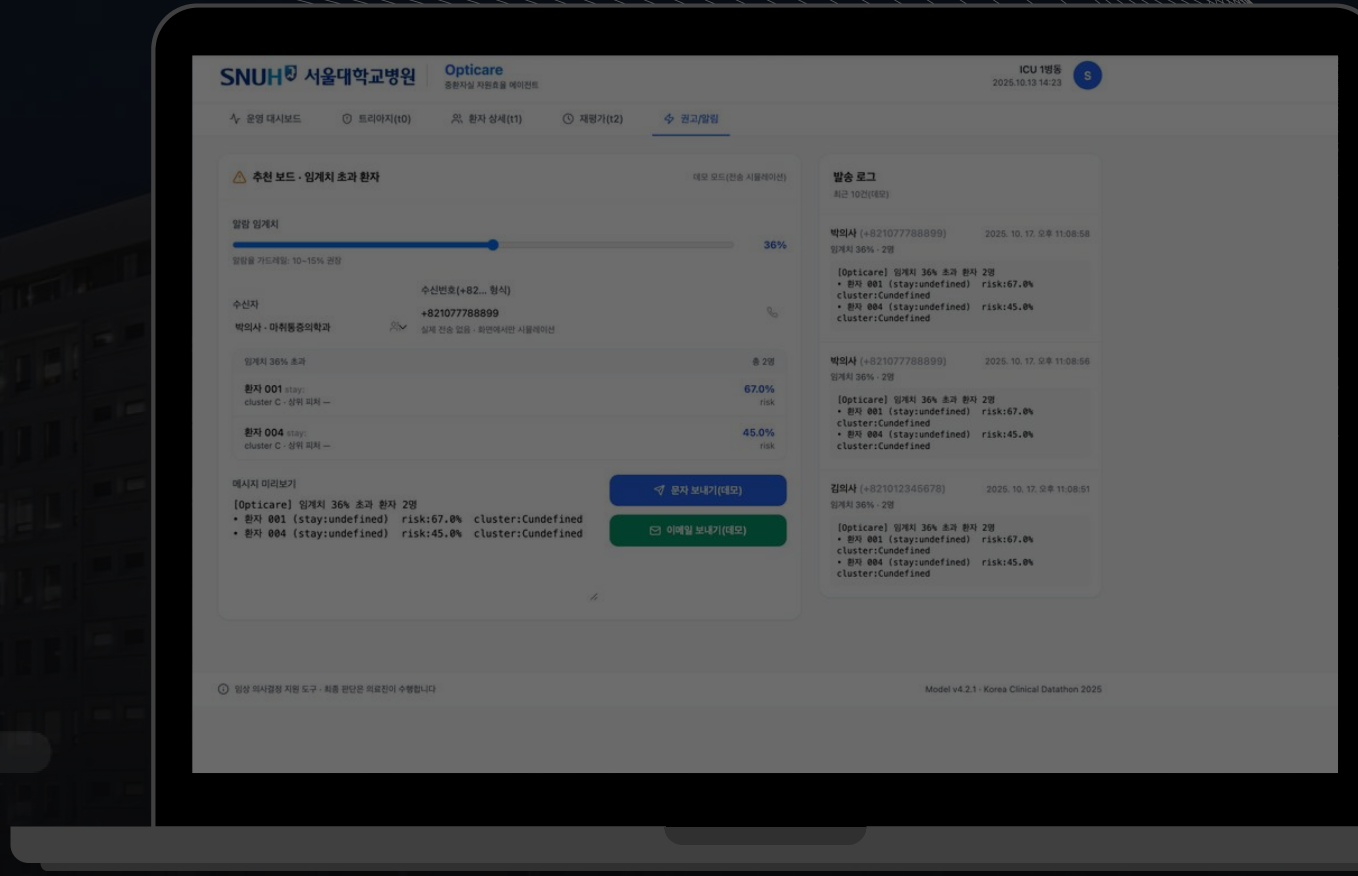
Agentic AI in Healthcare: Navigating Risks, Realizing Benefits

AICU

An ICU resource-efficiency agent that predicts risk, manages alert thresholds, and guides bed allocation across the patient journey



Thank you!



Appendix