HOSPITAL DA CRIANÇA DE BRASÍLIA JOSÉ ALENCAR

Critical Care Efficiency:

Data-Driven Solutions for Managing Capacity and Throughput

HOSPITAL DA CRIANÇA DE BRASÍLIA JOSÉ ALENCAR (HCB), BRAZIL

USC

Meet The Team

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Agenda

Project Scope

Background of HCB

Hospital Context

• Pediatric ICU in Brasília with 56 beds (20 isolation) across 4 wards
• Annual ICU admissions: 1,600–2,350
• LOS target: <9 days; actual ≈13.5 days
• Discharge delays due to lack of step-down capacity

Problem Statement

• Prolonged stays congest ICU flow and strain resources
• Delays in discharge + admission inefficiencies amplify bottlenecks
• Hospital lacks predictive tools to flag high-risk patients early

Stragetic Scope & Goals

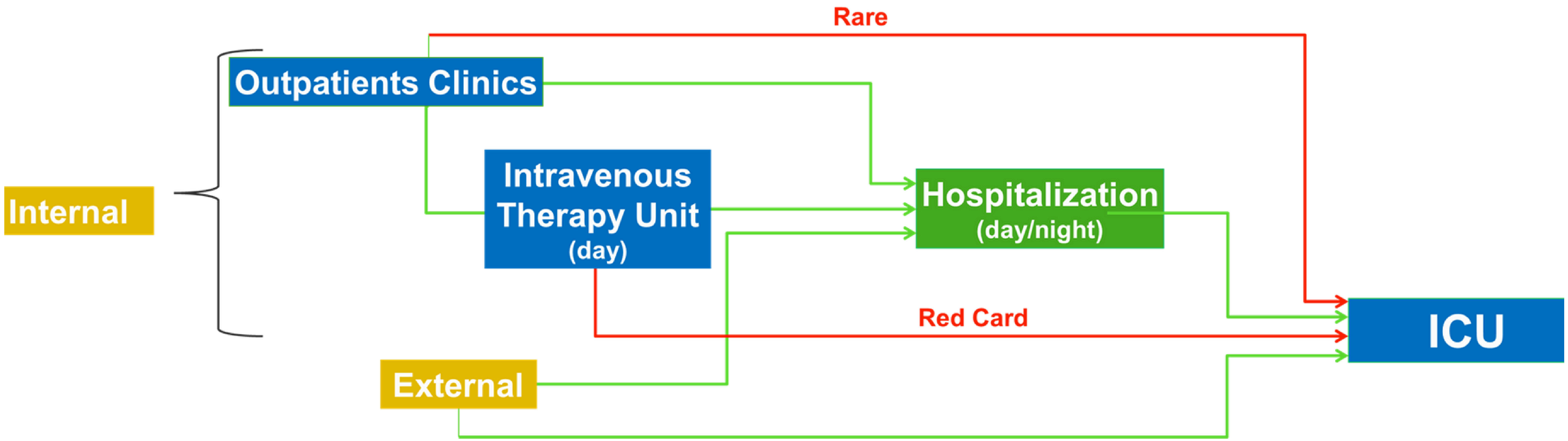
Scope of Work

- Analyze ICU LOS drivers using structured hospital data
- Integrate insights from site visit observations
- Prioritize bottlenecks in admission → discharge pathway

Project Goals

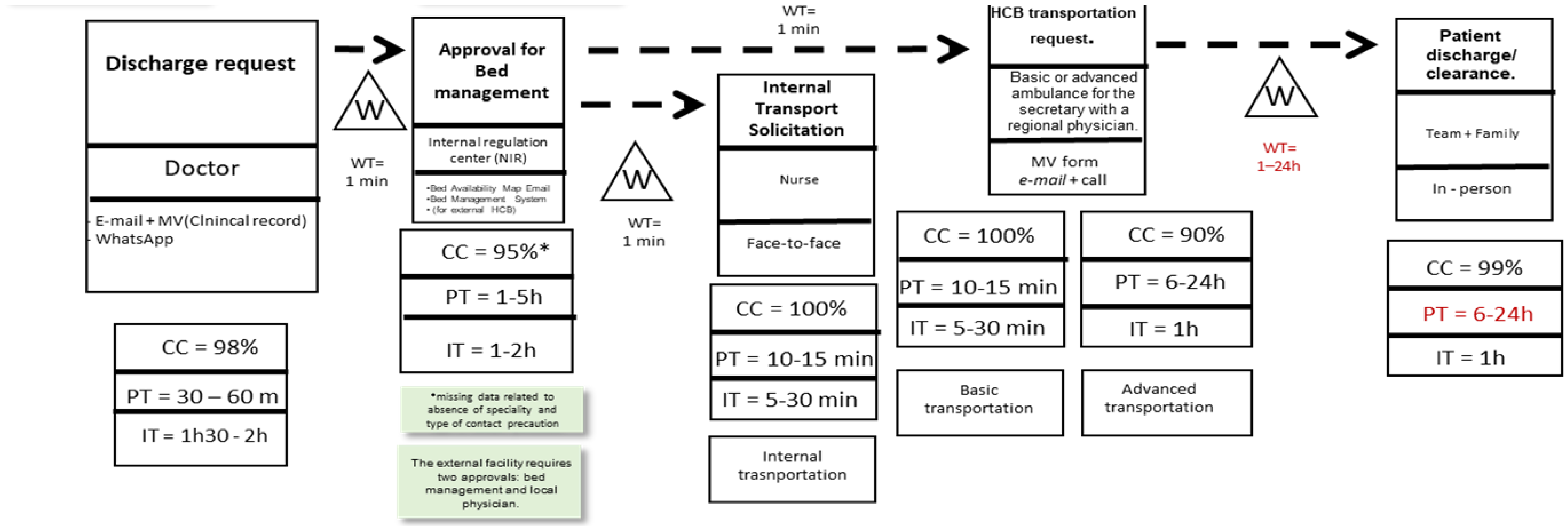
- Detect patterns by patient type, device usage, and diagnosis
- Forecast long-stay cases with admission-level data
- Propose scalable recommendations for ICU throughput

HCB ICU Admission Flow



This diagram (provided by HCB) illustrates the various pathways through which patients enter the ICU, distinguishing between internal and external sources and highlighting common vs. rare transitions. It helps contextualize patient inflow dynamics that influence ICU capacity and demand.

HCB ICU Admission Flow



WT		1 min		1 min			1-24h	
CC	98%		95%		100%	90%		99%
PT	30-60 min		1-5h		10-15 min	6-24h		6-24h
IT	1h30-2h		1-2h		5-30 min	1h		1h

This flowchart (provided by HCB) maps the step-by-step discharge process from the ICU, including approval, transport, and bed turnover logistics. It highlights potential operational bottlenecks that can delay discharge and affect bed availability for incoming patients.

Data Analysis

The Dataset

360 ICU cases | 2022–2024 | 19 variables total

Raw Data:

- *Sex*
- *Weight (kg)*
- *PIM III Result*
- *Expected Length of Stay*
- *Length of Stay*
- *Current Inpatient Unit*
- *Admission Date*
- *Movement Type*
- *Treatment Combo*
- *Admission Type*
- *Mechanical Ventilation*
- *Dialysis Required*
- *EVAT Recorded*

Data Cleaning & Feature Engineering Highlights

Feature Engineering

• LOS_Difference: Captures under-/overstay vs. expected LOS

• Readmitted_Flag: Flags patients who returned to ICU

• Admission_Weekday & Month: Tracks LOS drift over time

Data Cleaning

• Dropped rows missing key clinical inputs (e.g. PIM, EVAT)

• Parsed & standardized admission timestamps

• Label encoded key categorical fields (e.g. Sex, Unit)

Data Snapshot

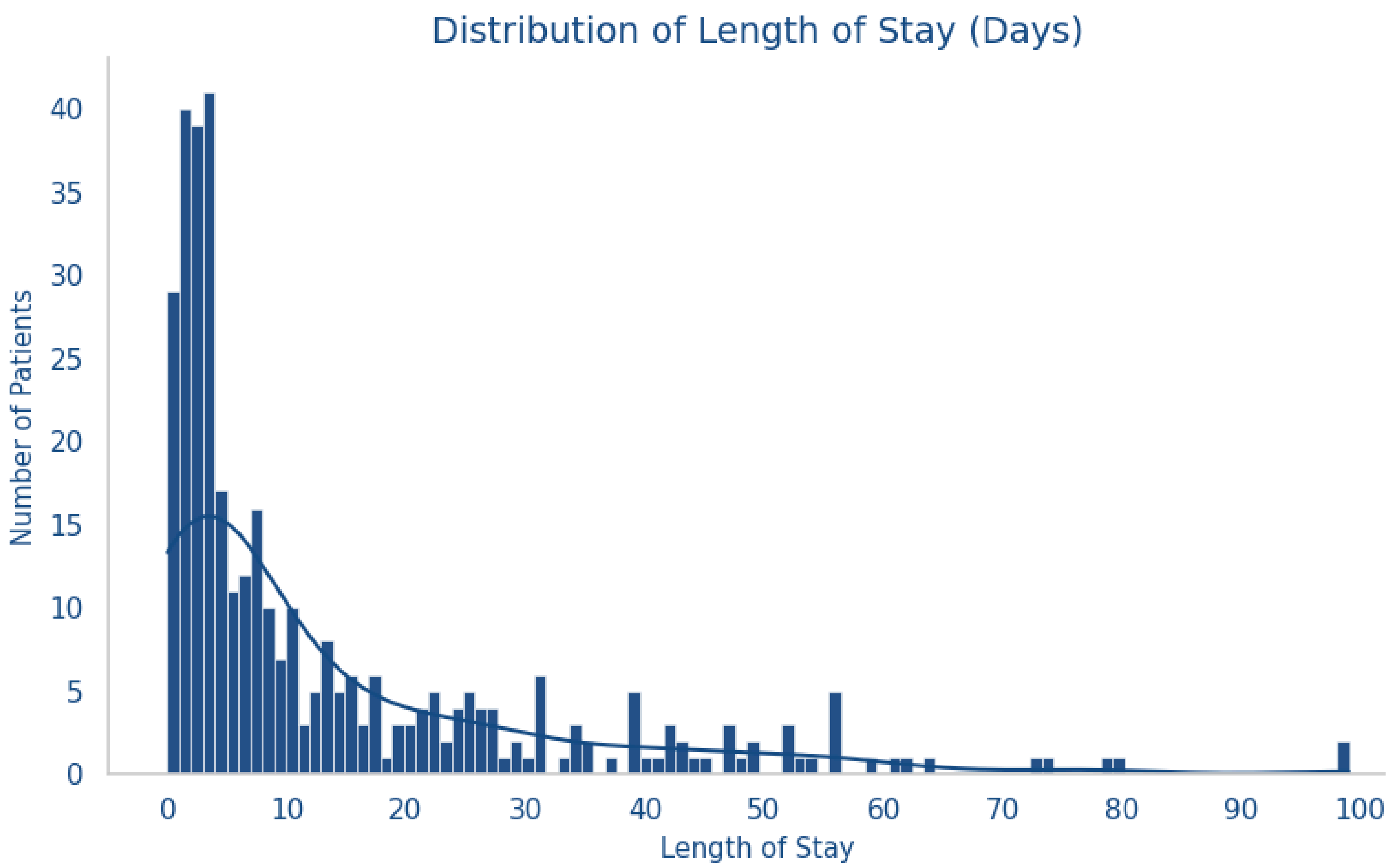
ICU Patient Variable Ranges

Variable	Min	Max	Range
Age	0	18	18
Weight (kg)	1.52	71.8	70.28
PIM Score	0.14	100	99.86
First ICU Stay (Days)	0	99	99
Readmission (Days)	0	106	106

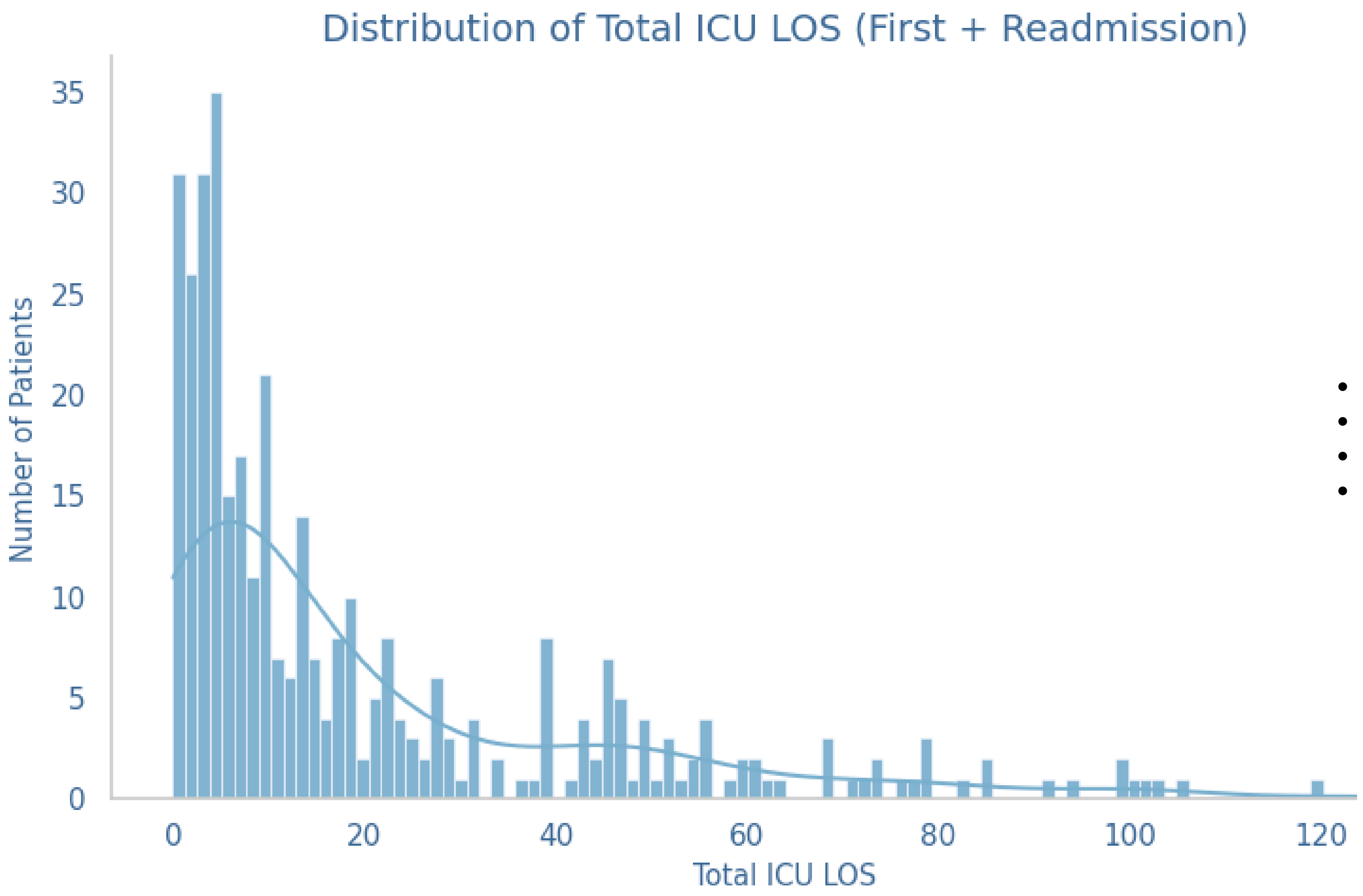
Who's in Our ICU Sample? (% Breakdown)

Variable	No. of Patients	% of Rows
Male	196	55%
Female	164	45%
ICU readmission	148	41%
Ventilation	233	64%
Dialysis	46	12%
Both ventilation and dialysis*	41	11%

LOS Distribution

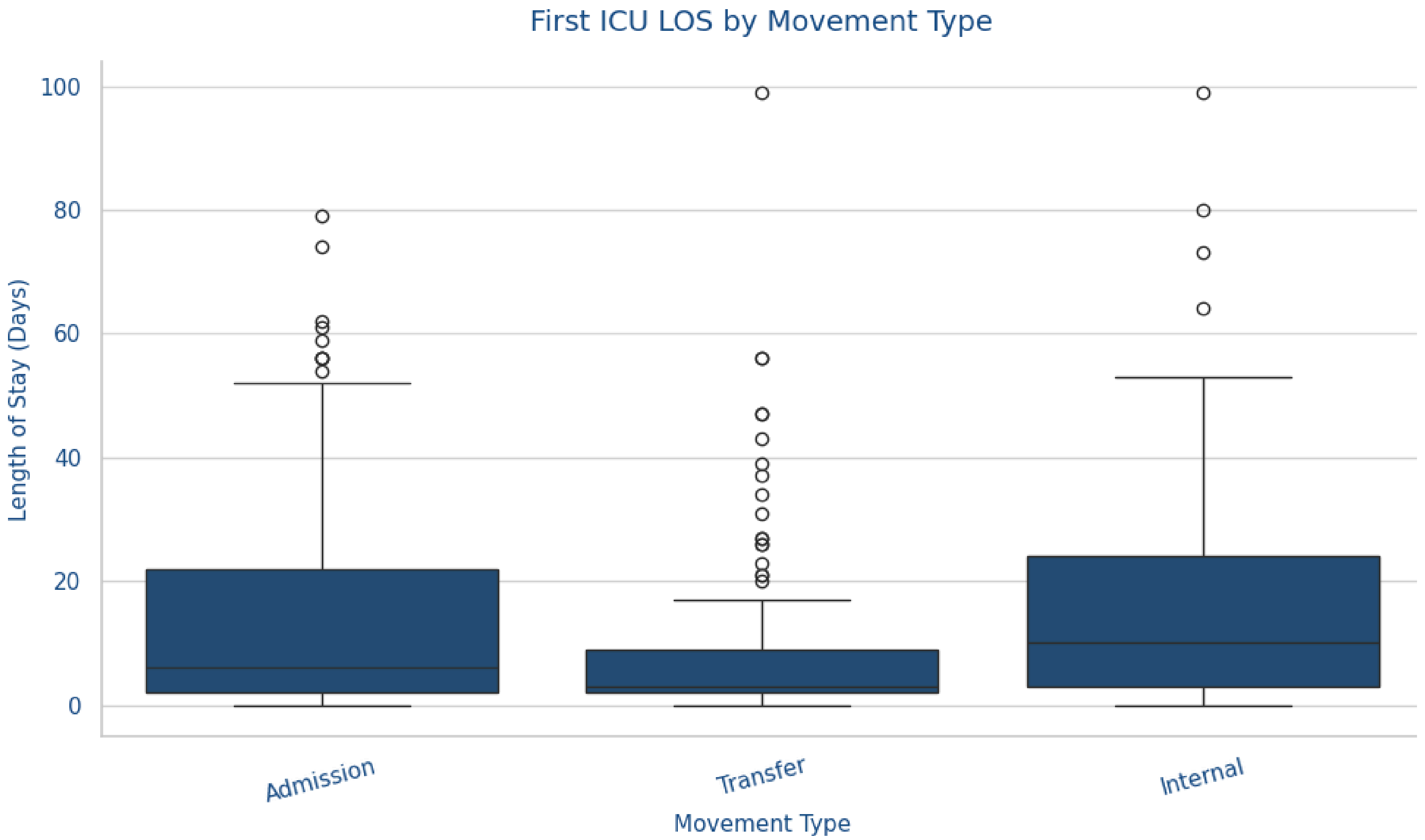


First ICU Stay: Nearly 70 % of patients leave the ICU in under 10 days, while a small tail of long-stay cases

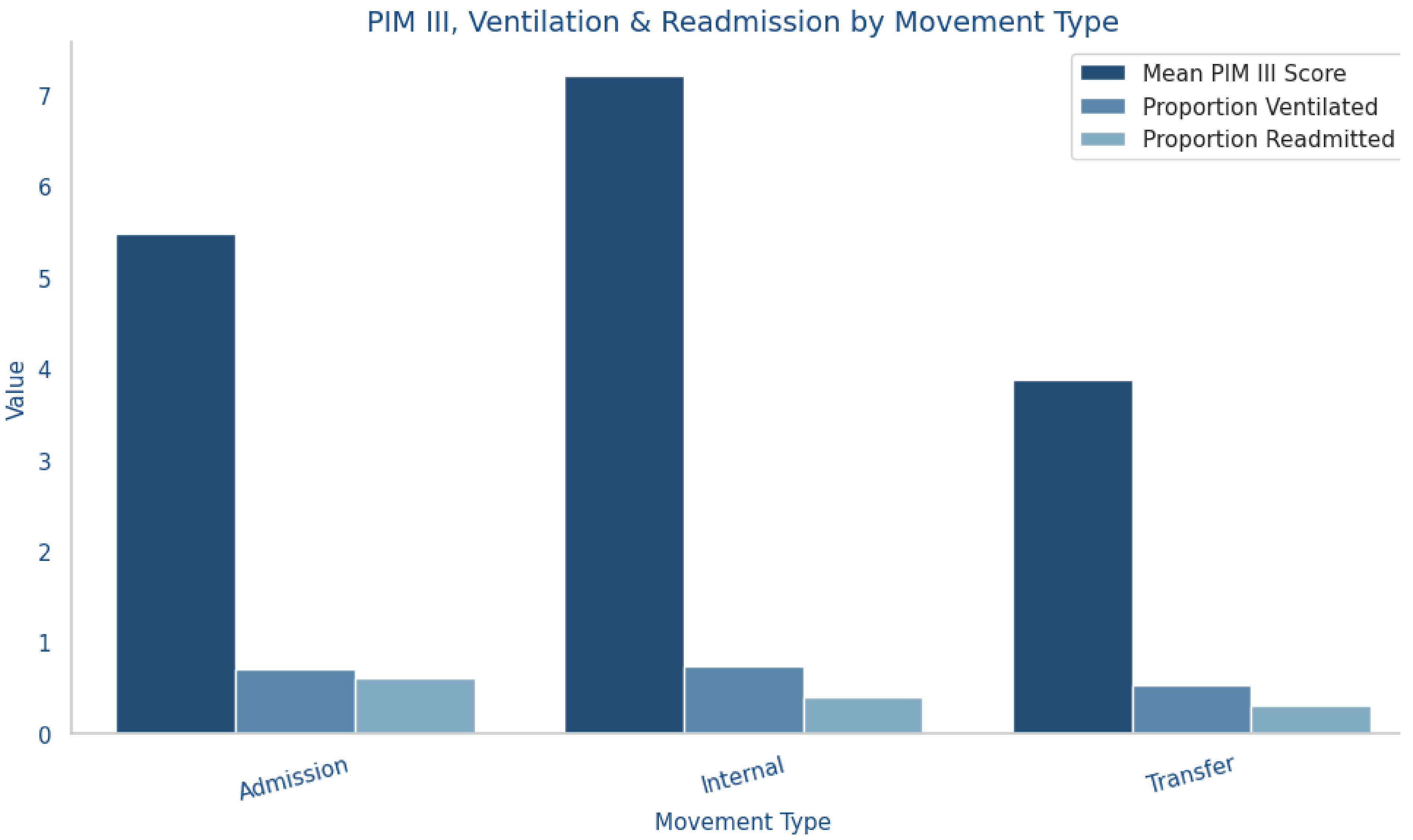


First + Readmission: Adding readmissions barely moves the curve, though they still account for the longest total stays

LOS by Admission Path



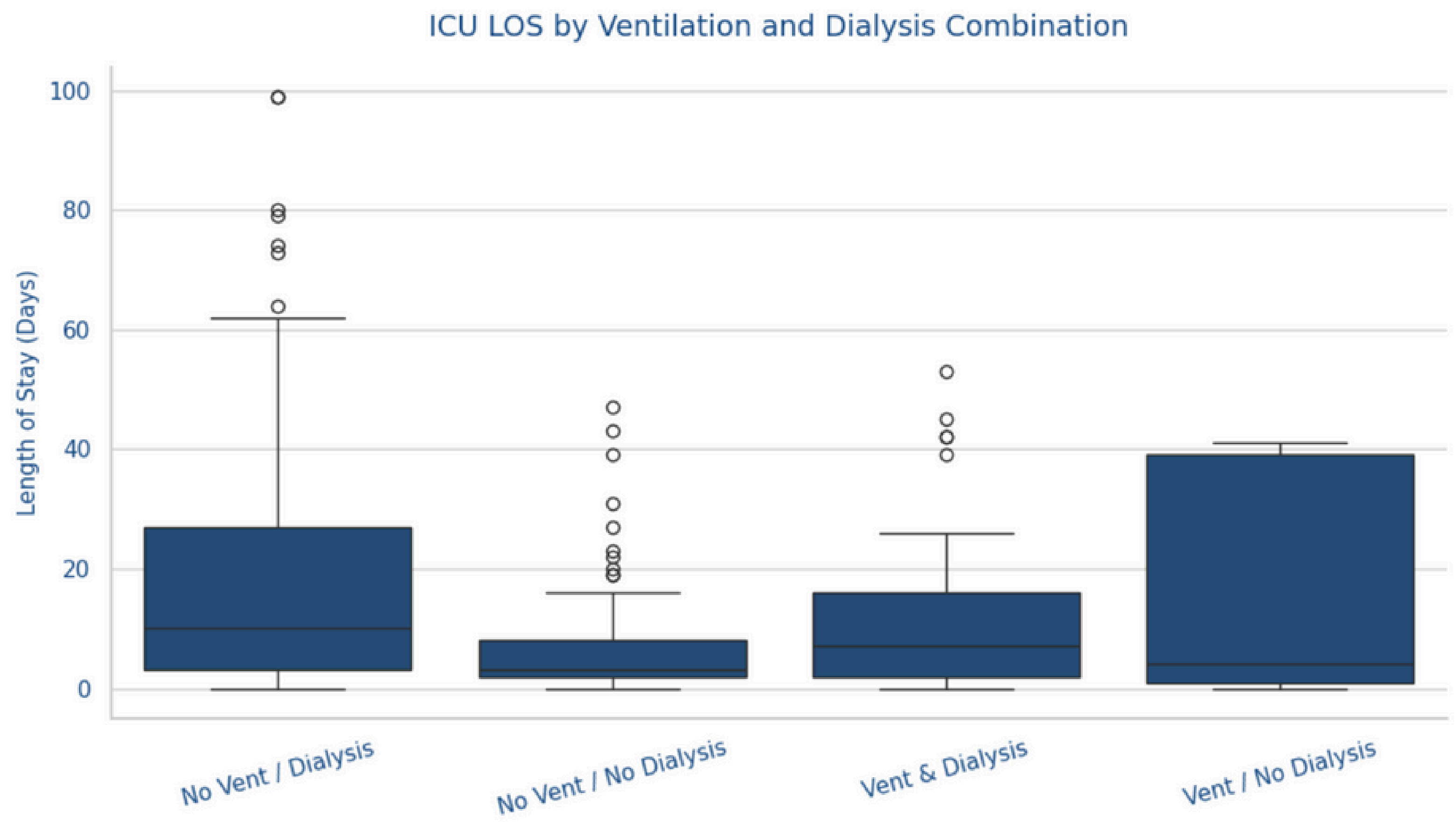
Direct & internal transfers stay longer in ICU than external ones

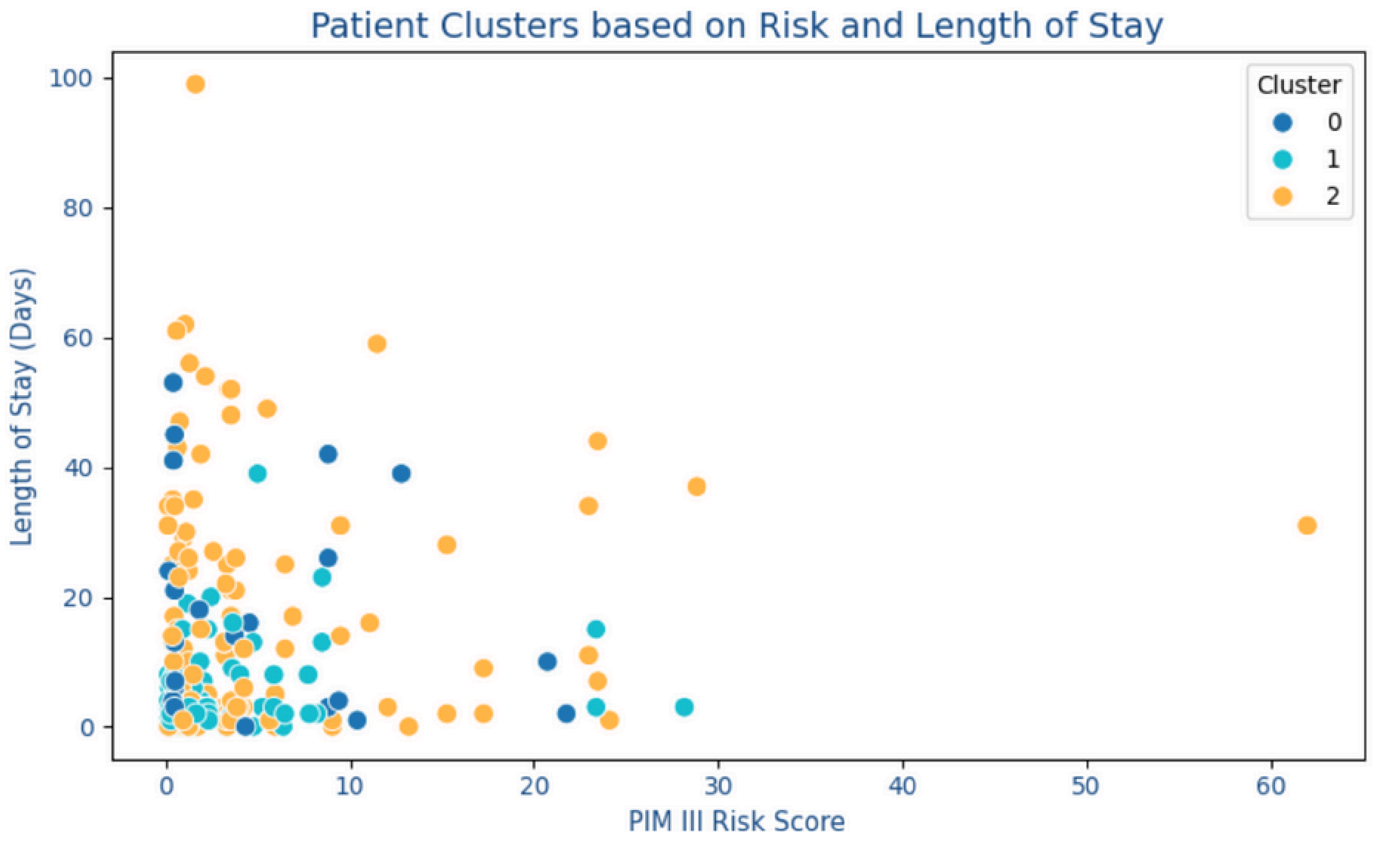


Direct admissions and internal transfers have higher PIM, use ventilators more, and get readmitted more than external transfers

LOS by PIM & Life Support Devices

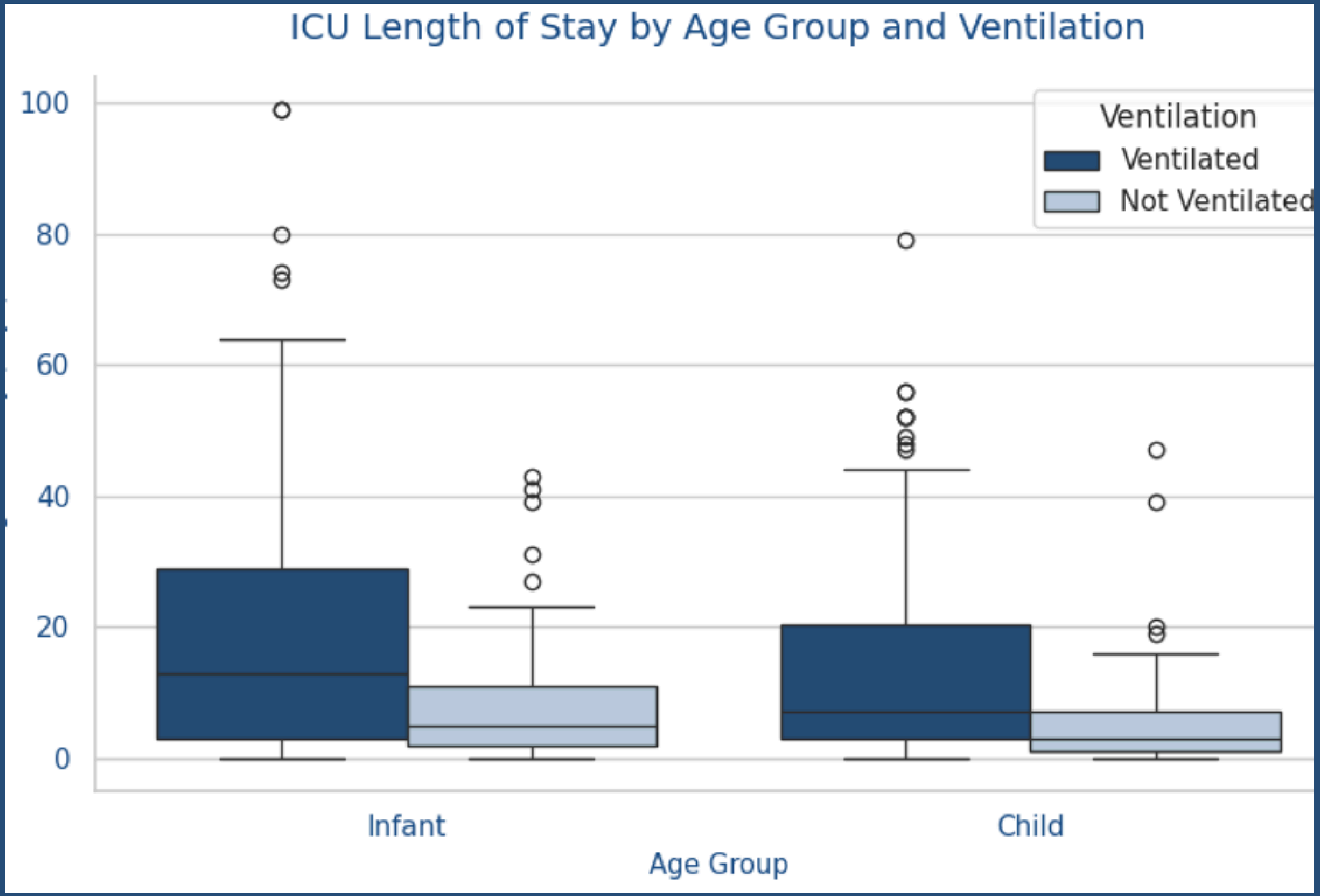
Patients needing both ventilation and dialysis have the longest ICU stays



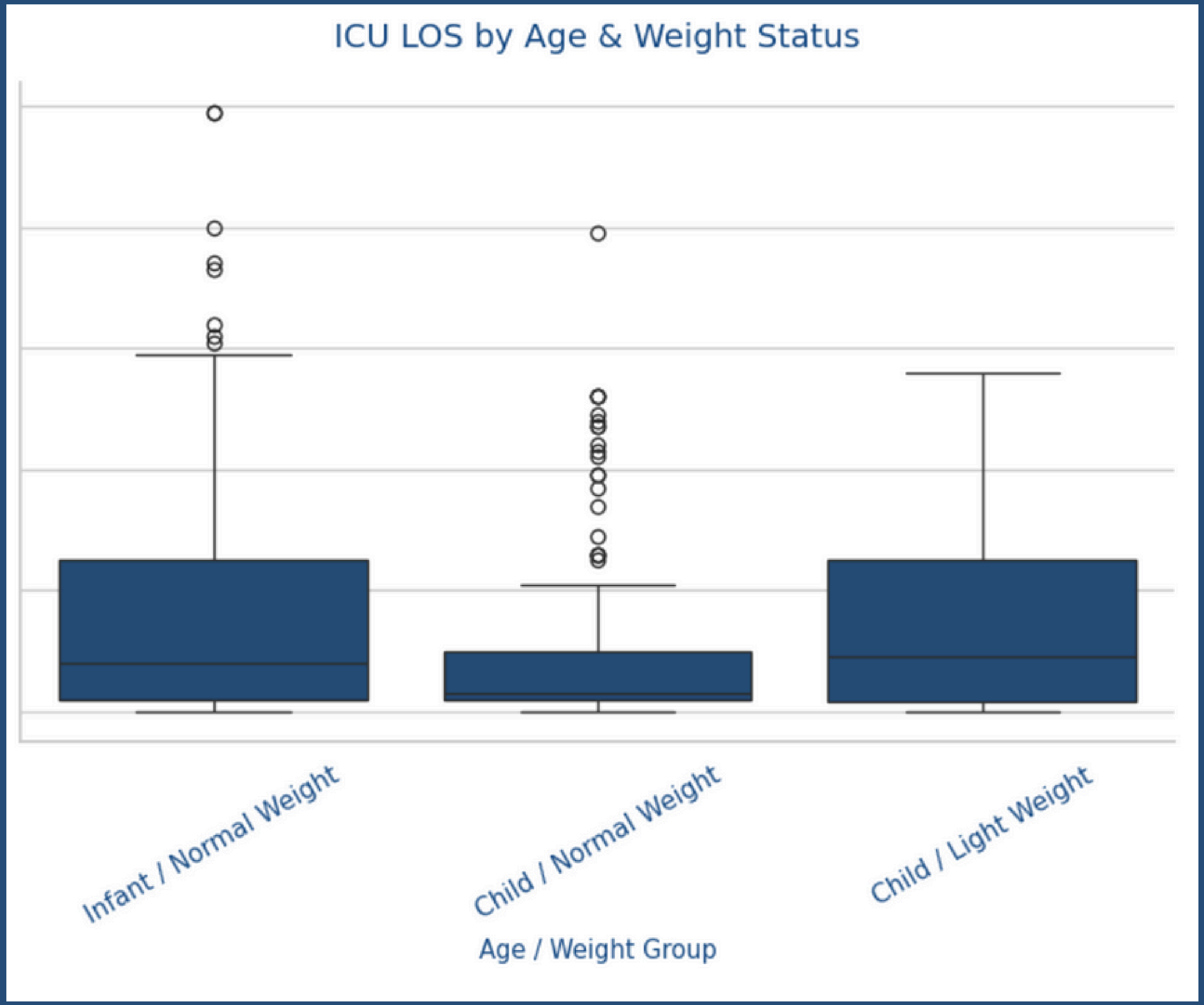


Higher PIM Score generally lands kids in the green cluster, which require more resources. Still, a few low-risk patients slip into long stays

LOS by Age Group

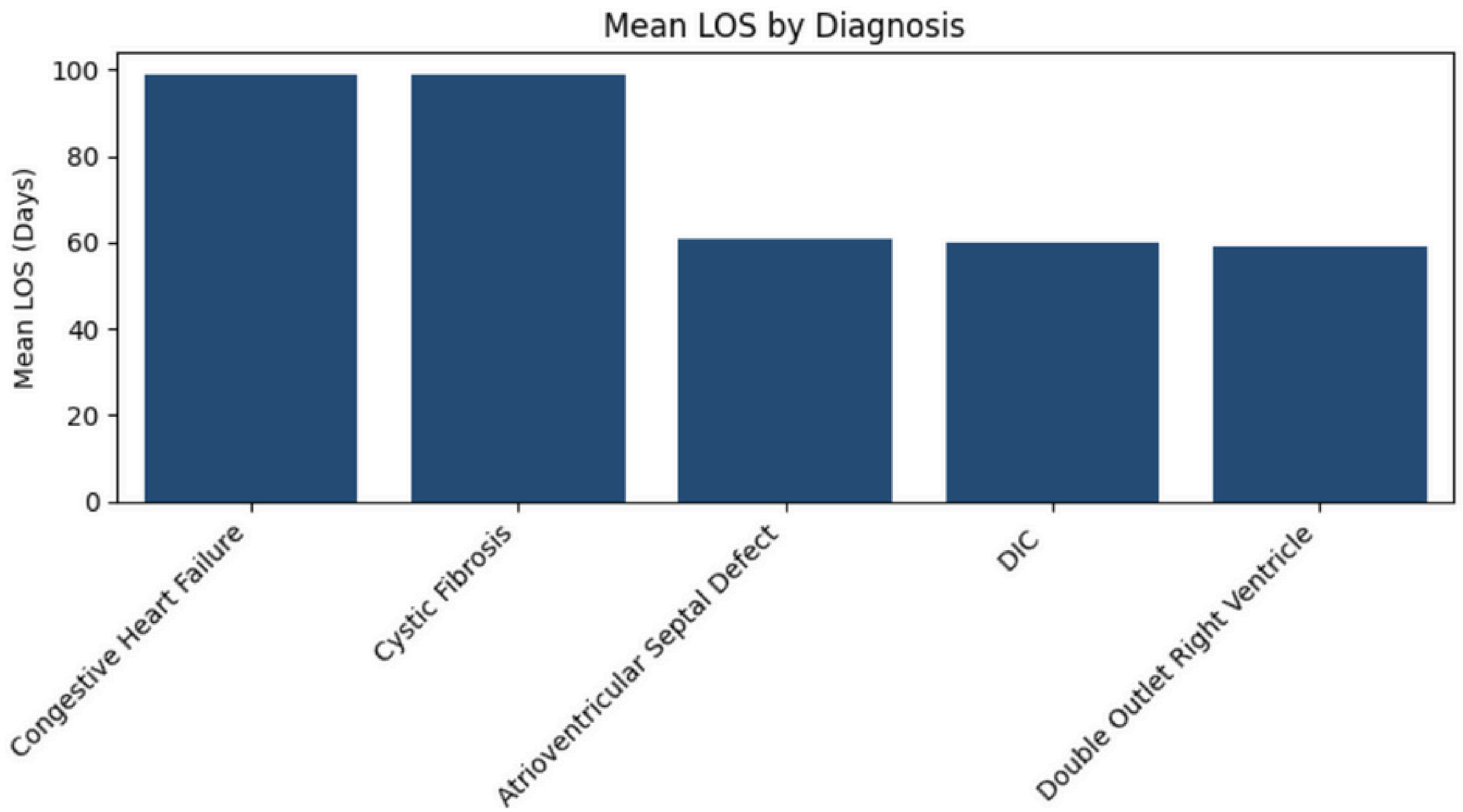


Ventilated infants top the LOS chart, whereas children without ventilation spend the least time in ICU

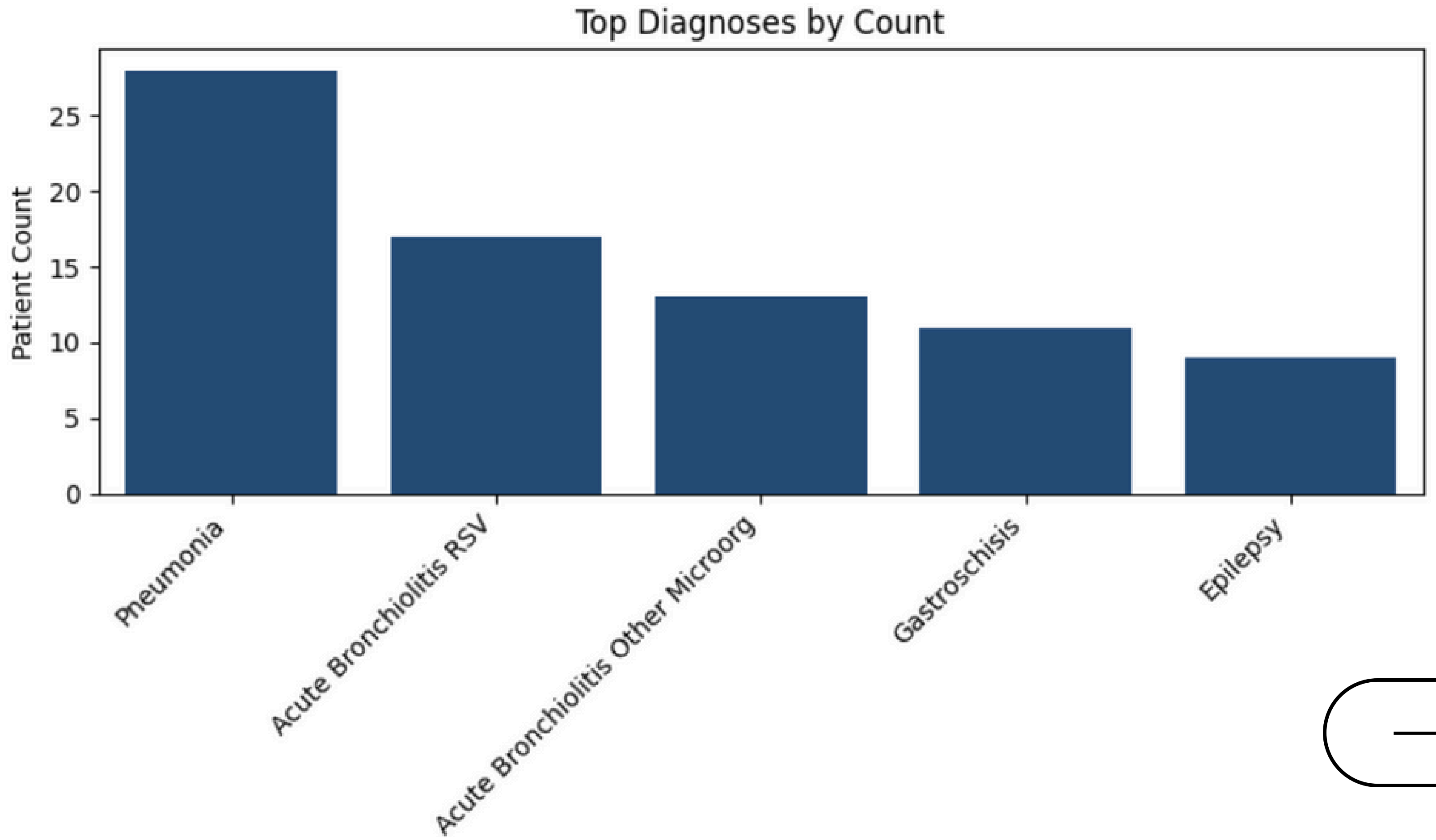


We see that infants below the median weight have the longest stays, while children with average weight tend to leave the ICU sooner

LOS by Type of Diagnosis



Heart failure and cystic fibrosis drive the longest ICU stays, averaging nearly 100 days, signaling high resource intensity compared to other diagnoses.



Blood poisoning and brain tumor cases drive the longest stays (≈23 days), while bronchiolitis and leukemia admissions average under 10 days

Modeling

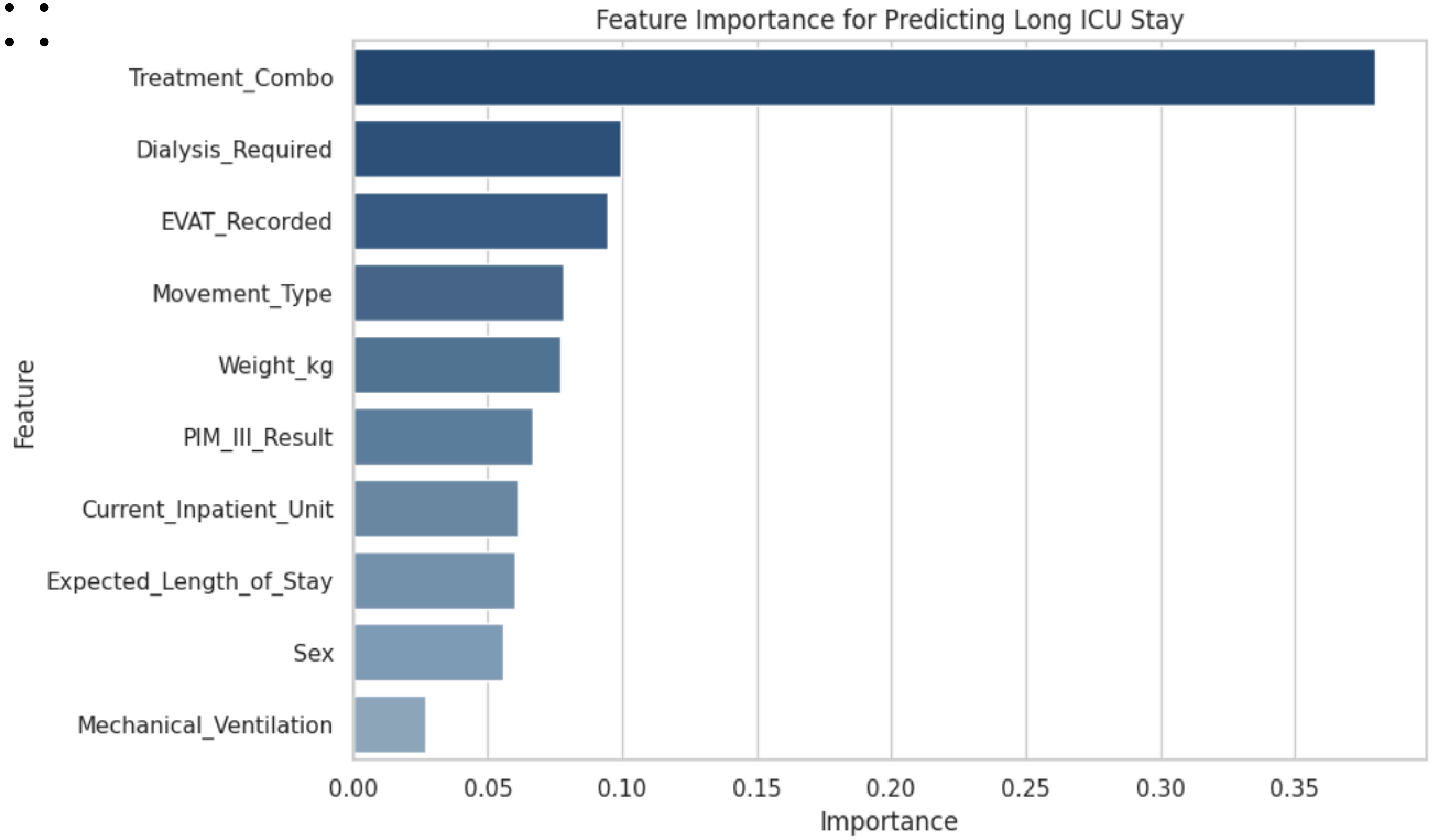
Forecasting Long ICU Stays Using Intake Data

Goal: Predict each patient's total ICU length of stay (LOS). Forecasts serve as the foundation for downstream bed utilization simulation

Scope: Utilized only pre-admission and admission data (no real-time vitals or labs)

Use Case: Helps clinical teams anticipate ICU demand and enables hospital planners to simulate expected bed occupancy over time based on projected intake and LOS forecasts

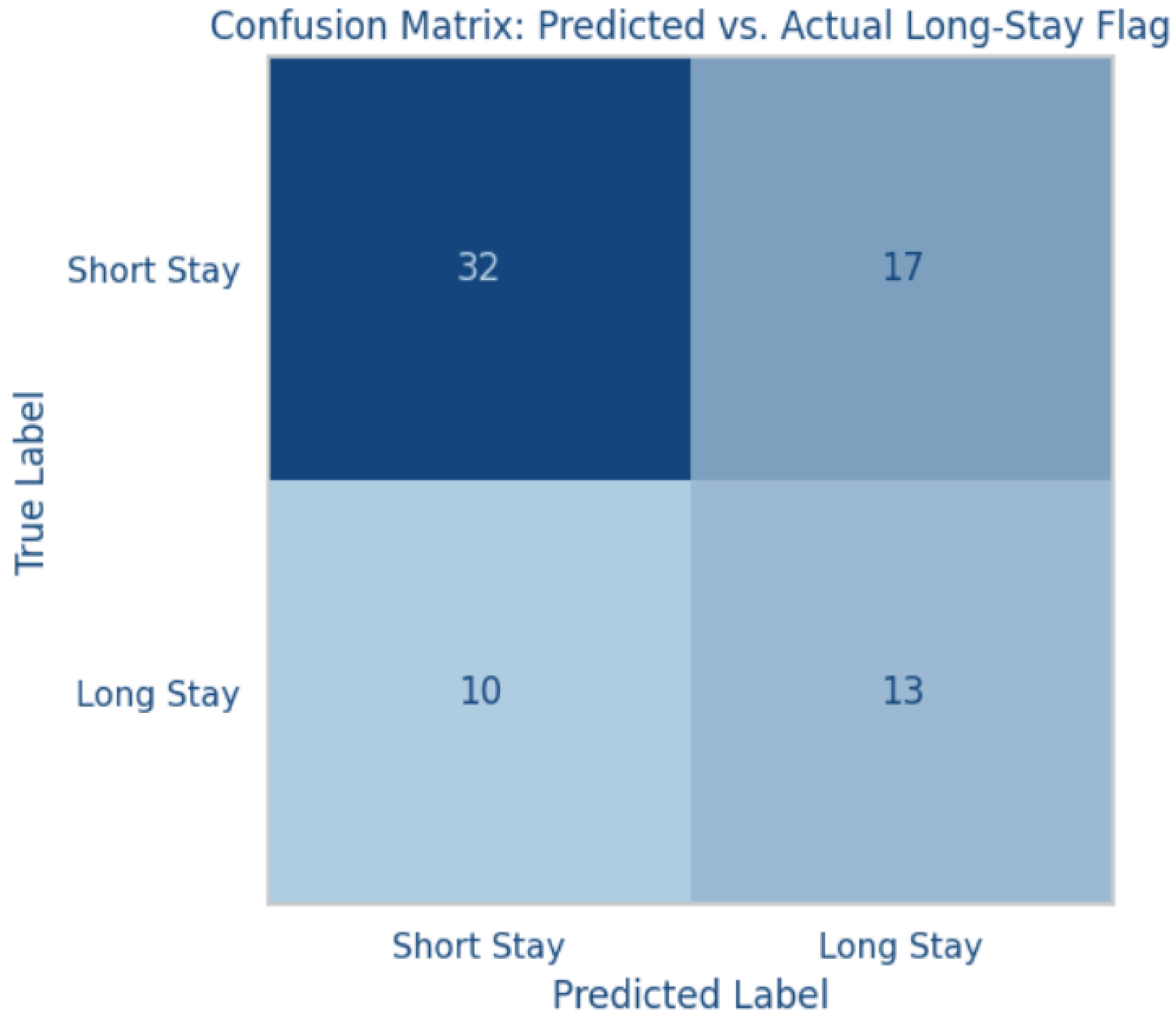
What Predicts Long ICU Stays?

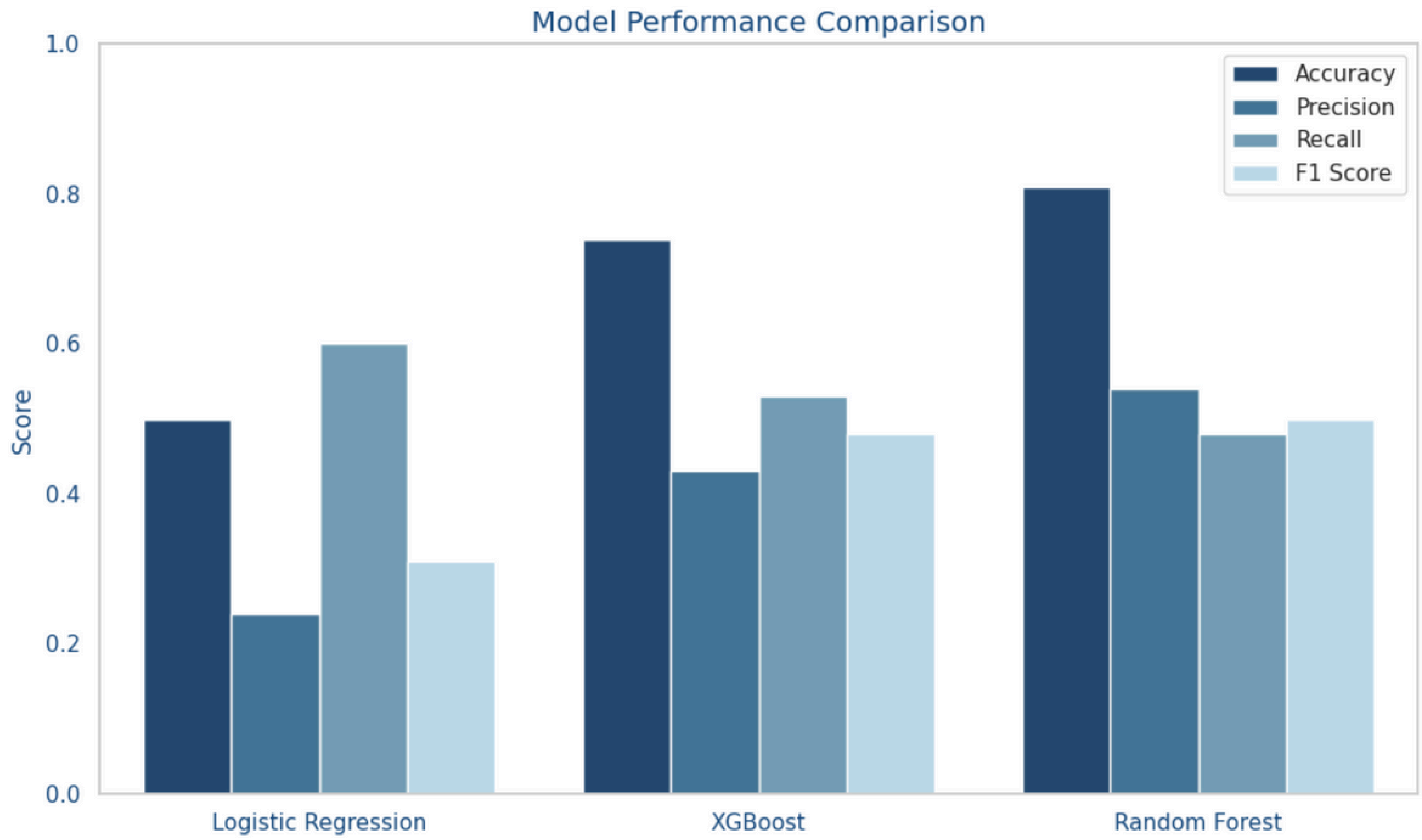


Clinical Insights Behind the Data:

- Ventilation and dialysis at intake signal higher patient complexity and acuity
- Direct and internal admissions are typically more severe, requiring greater resources
- These patterns are associated with longer ICU stays, offering early intervention opportunities
- Intake patterns also inform the simulation of cumulative bed demand at scale

Can We Reliably Predict Long ICU Stays?





Interpretable Scorecard for Early Risk Flagging

Patient receives 1 point for each of the following:

- On mechanical ventilation at admission
- Not transferred from another hospital
- PIM III score > 0.75 (clinical severity index)
- EVAT score not recorded
- Weight > 17 kg

If total score ≥ 4 → **Flagged as high-risk for extended ICU stay**

With limited resources available, this low-tech tool helps nurses quickly flag high-risk patients during shift huddles, no code needed.

Research-Backed ICU Stay Factors

(Saudi Arabia Study, 3,396 children under 14)

Factor	Odds of prolonged stay (> 30 days)	Take-away
Central-line infection (a serious blood infection)	OR ≈ 12.9×	Wasn't modeled. However, it was the biggest hit on LOS
Tracheostomy (incision in the Neck)	OR ≈ 7.7×	Early trach protocol worth exploring
Ventilation	OR ≈ 4.9×	Validates our "ventilation" risk flag
Transfer from another internal ward/ICU	OR ≈3×	Confirms transfer hand-off focus

Why does this matter to us?

- Some of the same red-flags flagged in our data also spike LOS in another children's ICU
- Strengthens our score-card & recommendations with outside proof

Building the Future of ICU Forecasting

Despite limited data, we built a scalable forecasting model that surfaces ICU risk before real-time monitoring begins, offering hospitals a powerful head start

Key Findings

- Random Forest showed the best performance (F1 ~0.55), signaling early promise
- Our intake-based framework offers a low-input way to forecast ICU length of stay without real-time vitals or labs
- Features like dialysis, ventilation, and internal admits were strong predictors of longer stays

Limitations

- A ransomware attack led to major data loss, especially among long-stay patients
- The reduced sample limited model accuracy and generalizability
- Still, the structure is scalable once data is restored or expanded

Conclusion: HCB's Priority Strategies

1. Frontline Scorecard for Real-Time Risk Flagging

- Flags high-risk patients at intake using 5 simple criteria (no vitals/labs needed)
- Enables early staffing, bed planning, and targeted care

Impact: More accurate bed forecasting, proactive resource allocation, earlier complex case identification

2. Prioritize Direct/Internal Transfers

- Tag and fast-track care for higher-acuity direct/internal admissions
- Allocate experienced staff and specialty consults early

Impact: Prevents bottlenecks, speeds triage, triggers early case management involvement

3. Scalable Predictive Modeling Pipeline

- 59% recall, 61% F1 score for identifying long-stay patients
- Structured for handoff, refinement, and Epic/dashboard integration

Impact: Sustains gains across teams, embeds predictive tools into workflow, supports LOS planning

Overall Outcomes:

Operational: Better resource planning, reduced bottlenecks, streamlined workflows
Clinical: Faster high-acuity patient identification, improved care coordination, targeted interventions

Thank You

Do you have any questions?

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