



Bridging the Gap: Forecasting ICU Demand and Readmission Risk Using MIMIC Data

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Introduction



ED Crowding Delays Critical Care

Overcrowding makes early deterioration harder to detect, causing some patients to worsen within hours and require urgent ICU transfer.

ICU Strain Raises Mortality

Delays in escalation or premature ICU discharge increase mortality risk and lengthen hospital stays.

Need for Short-Term ICU Capacity Planning

Hospitals need real-time ICU demand forecasting to support safe triage, timely discharge, and resource allocation.

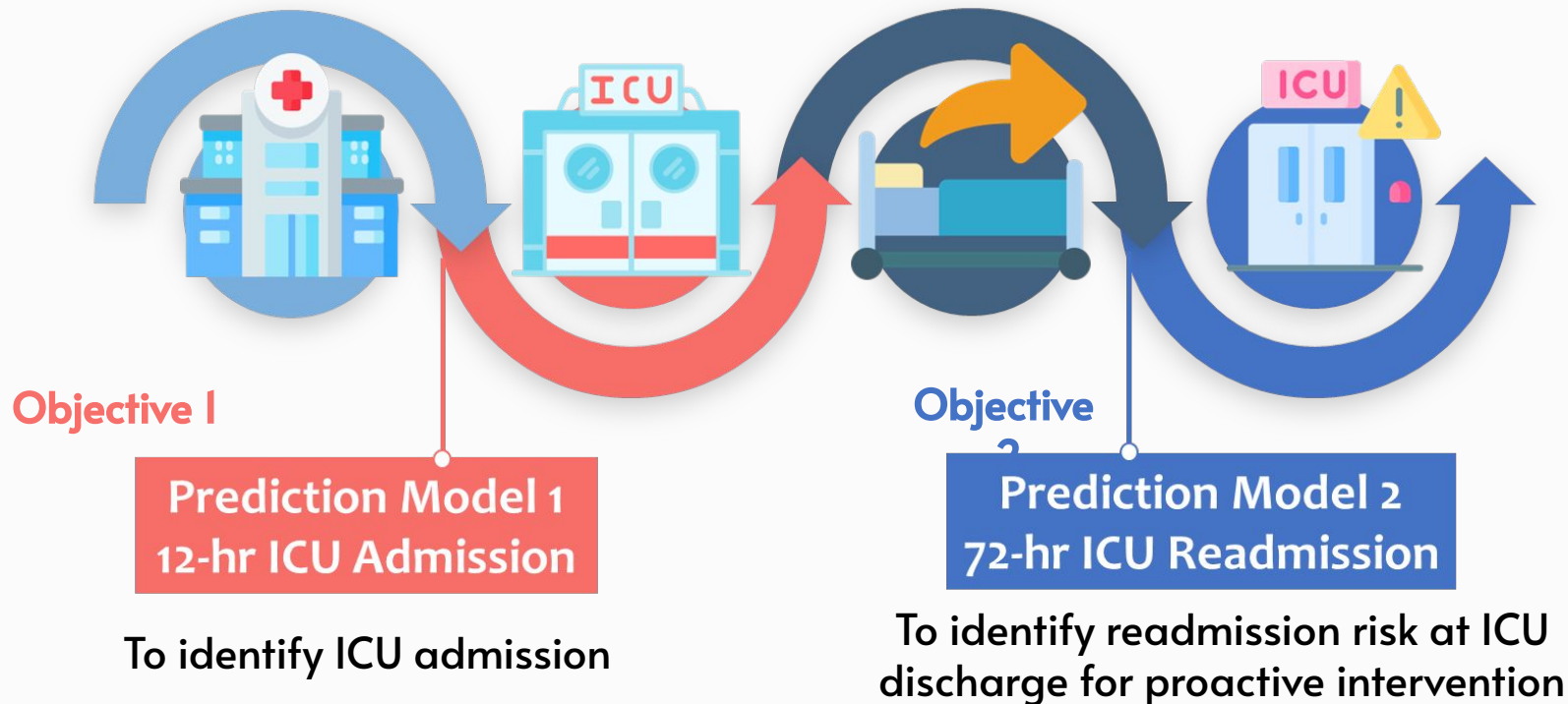
| Literature Review | | | | |
|---------------------|--|--|--------------|--|
| Author/Year | Study focus | Method | Result (AUC) | Clinical impact |
| Hu et al., 2025 | Predict ICU readmission within 72h | XGBoost + structured + radiology-note embeddings | 0.78 | Outperformed SWIFT; multimodal features improve prediction |
| Nguyen et al., 2021 | Predict ICU need within 24h after inpatient admission | ML using EHR (vitals, labs, orders, dx codes) | 0.82-0.88 | Better than ESI; vital signs most predictive |
| Glass et al., 2021 | Predicting ED→ICU transfer within 24h | Logistic regression using vitals + labs | 0.70 | Baseline performance for early deterioration detection |
| Gidari et al., 2020 | Predicting in-hospital ICU admission among COVID-19 patients | NEWS2 early warning score | 0.90 | Shows vital signs can signal deterioration |

Problem Statement & Gap



| | |
|---|---|
| 1 | Early ICU needs in the ED must be identified quickly, yet current tools (e.g., EWS, vitals-only scores) remain limited. |
| 2 | Predicting 72-hour ICU readmission is still challenging, even with modern ML models, leaving a safety risk after ICU discharge. |
| 3 | Existing models treat ED→ICU and ICU→ward transitions separately, hindering short-term resource planning. |

Objective





Method

Data Source

PhysioNet



- MIMIC-IV-ED v2.2 —
ED triage, initial diagnoses, early medications
- MIMIC-IV v3.1 —
admissions, transfers, ICU stays, labs, clinical events
- Record linkage:
subject_id and hadm_id used to integrate ED and hospital data

Dataset we used

HOSP

- admissions- basic admission info
- transfers- timestamped location changes
- patients- core demographic/ mortality info

ICU

- icustays- icu level encounter records
- dateimeevents- icu time series clinical events
- inpuvents- detailed medication/ IV records

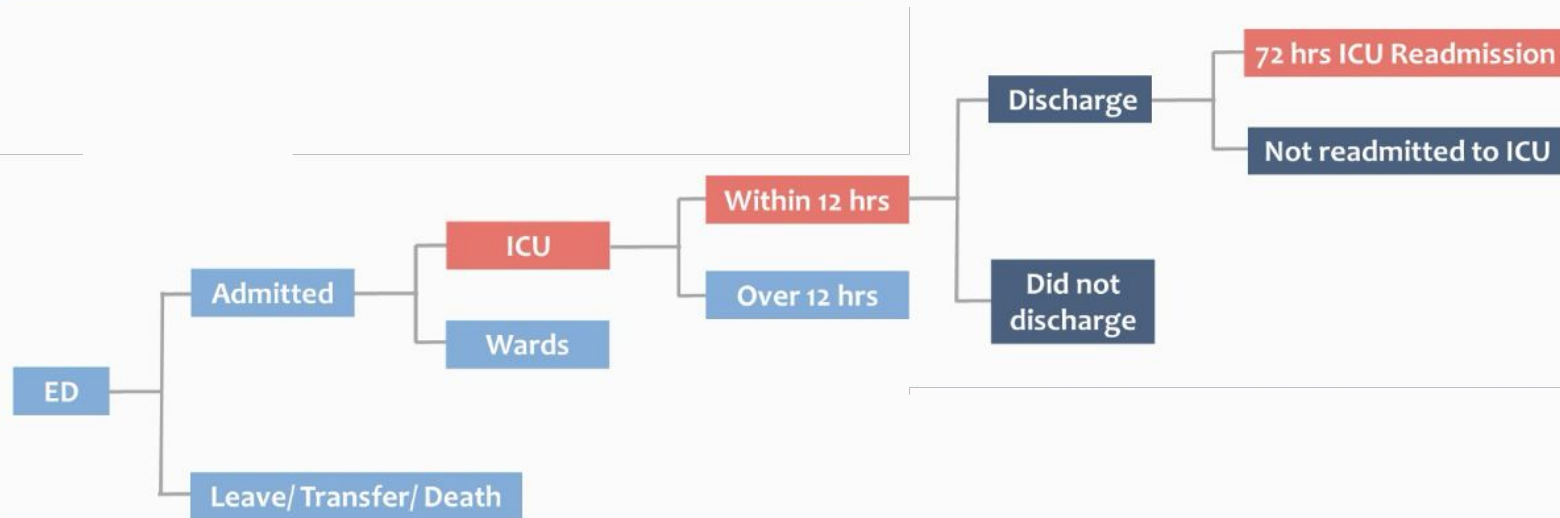
Study Design

(ED → ICU)

(ICU → Discharge → Readmission)

Phase 1 Upstream

Phase 2 Downstream



- Cohort: ED visits → hospital admission
- Dependent Variable: `icu_within_12h`
- Negative: ward admission OR ICU after 12h

- Cohort: phase 1 positives + survived ICU stay
- Dependent Variable: `readmission_72h`
- Excluded: unit-to-unit transfers

Feature Engineering

ICU Stay Processing

- Length of Stay (LOS) is calculated using the ICU admission time (intime) and discharge time (outtime).

Triage Processing

- Standardizing pain scores
- Chief-complaint normalization → top 25 categories

Medication Feature Engineering

- Mapping >1,000 drug names → 22 pharmacologic classes
- Extracting class-level counts

Modeling

XGBoost

Evaluation Metrics

**AUC, Accuracy,
Recall, Precision**



Results

Descriptive Results

Demographics

Key Differences between ICU & Non-ICU Groups:

- **Demographics:**
 - Older (62 vs 49 years), male-predominant (54% vs 45%)
 - More likely white (64% vs 57%) and married (40% vs 16%)
 - Medicare-insured (55% vs 20%)
- **Arrival Pattern:**
 - Ambulance transport (64.1% vs 34.4%)
 - Walk-in less common (21.4% vs 62.3%)
- **Clinical Outcomes:**
 - Shorter ED stay (5.6 vs 7.3 hours)
 - Higher 30-day mortality rate (15.3% vs 1.0%)

Table 1. Baseline Characteristics between ICU and Non-ICU Groups

| Characteristics | ED - ICU | | ED – Non-ICU | | P-Value |
|---------------------------|----------|------|--------------|------|---------|
| | N | % | N | % | |
| N (%) | 31,915 | 7.5 | 393,138 | 92.5 | |
| Age (Mean ± SD) | 62.4 | 17.7 | 49.4 | 20.0 | <0.001* |
| Gender | | | | | |
| Male | 17,319 | 54.3 | 177,849 | 45.2 | <0.001* |
| Female | 14,596 | 45.7 | 215,289 | 54.8 | <0.001* |
| Race | | | | | |
| White | 20,462 | 64.1 | 225,522 | 57.4 | <0.001* |
| Black | 4,378 | 13.7 | 88,609 | 22.5 | <0.001* |
| Asian | 1,086 | 3.4 | 17,441 | 4.4 | <0.001* |
| Hispanic/Latino | 1,291 | 4.0 | 33,219 | 8.4 | <0.001* |
| Others | 4,698 | 14.7 | 28,347 | 7.2 | <0.001* |
| Marital Status | | | | | |
| Married | 12,794 | 40.1 | 62,760 | 16.0 | <0.001* |
| Single | 10,080 | 31.6 | 72,266 | 18.4 | <0.001* |
| Widowed | 4,173 | 13.1 | 20,031 | 5.1 | <0.001* |
| Others | 4,868 | 15.3 | 238,081 | 60.6 | <0.001* |
| Insurance | | | | | |
| Medicaid | 5,423 | 17.0 | 36,985 | 9.4 | <0.001* |
| Medicare | 17,683 | 55.4 | 77,279 | 19.7 | <0.001* |
| Private | 7,307 | 22.9 | 49,029 | 12.5 | <0.001* |
| Others | 1,502 | 4.7 | 229,845 | 58.5 | <0.001* |
| Arrival Transport | | | | | |
| Ambulance | 20,447 | 64.1 | 135,288 | 34.4 | <0.001* |
| Helicopter | 612 | 1.9 | 256 | 0.1 | <0.001* |
| Walk in | 6,836 | 21.4 | 244,999 | 62.3 | <0.001* |
| Others | 4,020 | 12.6 | 12,595 | 3.2 | <0.001* |
| ED LOS, hours (Mean ± SD) | 5.6 | 3.7 | 7.3 | 6.6 | <0.001* |
| 30-Day Mortality | 4,888 | 15.3 | 4,020 | 1.0 | <0.001* |

Predictive Modeling Results

Model 1 12-hr ICU Admission

AUC

0.96

Accuracy

0.87

Recall

0.93

Precision

0.30

Model Interpretation

- The model shows strong discrimination (AUC = 0.96)
- High recall (0.93) indicates it can successfully identify most patients who will require ICU care
- Low precision (0.30) reflects many false positives, likely due to the rarity of true ICU transfers

Model 2 72-hr ICU Readmission

AUC

0.72

Accuracy

0.79

Recall

0.52

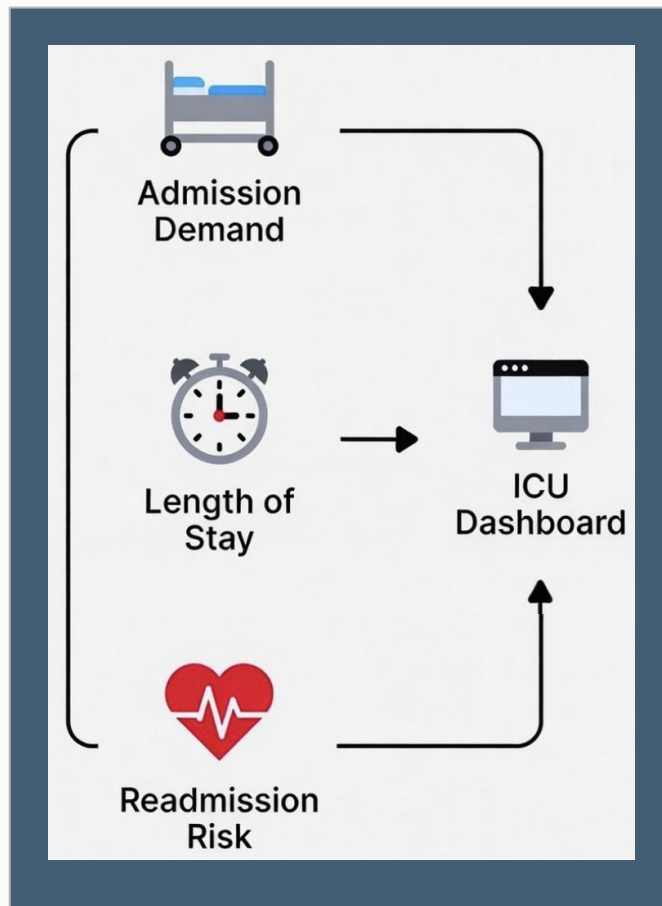
Precision

0.12

Model Interpretation

- The model shows moderate discrimination (AUC = 0.72)
- Recall is low (0.52), meaning many true readmissions are still hard to detect
- Very low precision (0.12) reflects the rarity and complexity of post-ICU deterioration

Combine Models: ICU Bed Demand Forecasting Framework



1 Model 1 - 12-hr ICU Admission Demand

Assigns each ED patient a probability of requiring ICU care within 12 hours. Aggregating these **provides a short-term estimate of incoming ICU demand**

2 ICU Length of Stay

Uses historical LOS data to **estimate how long ICU beds remain filled**

3 Model 2 - 72-hr ICU Readmission Risk

Assess discharge suitability and flag patients who are likely to return, **improving short-term estimates of incoming ICU**

4 ICU Dashboard

Offers a complete view of ICU patient flow and helps clinicians anticipate demand, allocate resources, and manage discharge timing

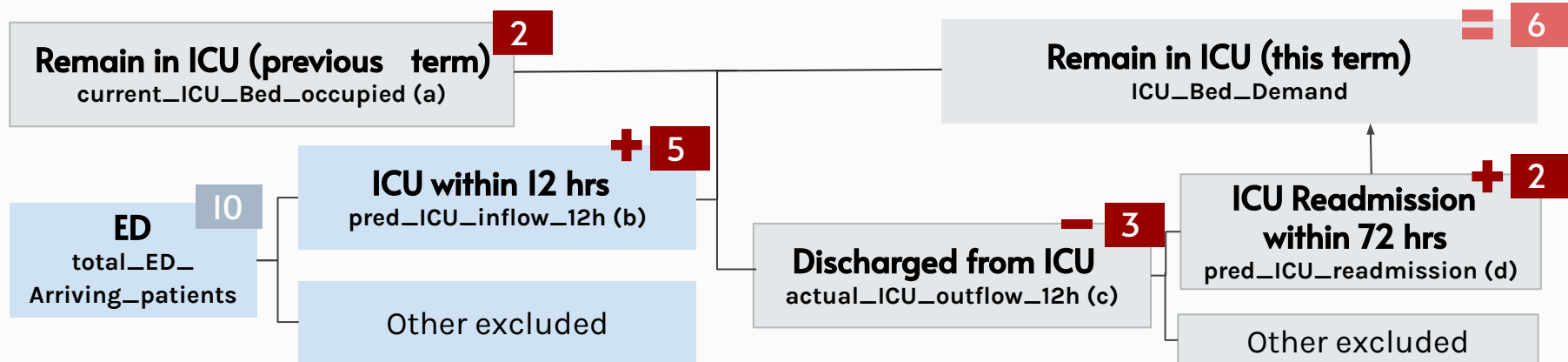
Demo- ICU Bed Forecast Result

(ED → ICU)

(ICU → Discharge → Readmission)

Phase 1 Upstream

Phase 2 Downstream



| timestamp | total_ED_Arriving_patients | current_ICU_Bed_occupied (a) | pred_ICU_inflow_12h (b) | actual_ICU_outflow_12h (c) | Pred_ICU_readmission (d) | ICU_Bed_Demand (a+b-c+d) |
|----------------|----------------------------|------------------------------|-------------------------|----------------------------|--------------------------|--------------------------|
| 2150/9/1 12:00 | 10 | 2 | 5 | 3 | 2 | 6 |
| 2150/9/2 00:00 | 4 | 6 | 0 | 0 | 0 | 6 |
| 2150/9/2 12:00 | 11 | 6 | 3 | 1 | 0 | 8 |



Discussion & Conclusion

Key Contribution

- Integrated ED-to-ICU admission and ICU readmission prediction into one forecasting framework
- Achieved strong performance for early ICU admission prediction using ED data alone (AUC 0.96)
- Demonstrated a proof-of-concept ICU capacity forecasting system combining predicted inflow, LOS, and readmission risk

Study Limitations

- Limited Generalizability- MIMIC-IV originates from one hospital
- Timestamp Shifting- MIMIC-IV dates are shifted into the 2100–2200 range which may affect time-dependent features
- Proof-of-Concept Framework- Deployment requires LOS prediction + multi-site validation

Key Findings

- Routine EHR data predicts ICU admission (AUC 0.96) and readmission (AUC 0.72)
- Triage features provide early signals of deterioration
- Framework connects ED inflow, ICU occupancy, and readmission risk
- Models offer practical decision support for triage and ICU discharge planning, helping anticipate bed shortages and reduce unsafe discharges.

Future Work

- Multi-site validation using real-time clinical data
- Real-time deployment with streaming prediction pipelines
- LOS prediction model to replace LOS for accurate capacity forecasting
- Richer data inputs (notes, labs, physiological trends, imaging) to improve performance

References

- [1] Glass, G. et al. (2021). *Dynamic data in the ED predict requirement for ICU transfer following acute care admission*. Crit. Care, 25(1): 123. [PMCID: PMC8145085]
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- [3] He, S. et al. (2021). *Developing machine learning models to personalize care levels among emergency room patients for hospital admission*. J. Am. Med. Inform. Assoc., 28(11): 2423–2431. [PMCID: PMC8561936]
- [4] Hu, H. et al. (2025). *ReAdmit: Predicting early unplanned ICU readmission using radiology notes and structured data*. Nurs. Crit. Care, 30(6): e70200. [PubMed]
- [5] Ruppert, M.M. et al. (2023). *Predictive modeling for readmission to intensive care: a systematic review*. Crit. Care Explor., 5(1): e0848. [PubMed: 36723728]

Thank you.

ICU Bed Forecast Results

| timestamp | total_ED_ arriving_patient s | Current_ICU_ Bed_occupied | pred_ICU_ inflow_12h | actual_ICU_ inflow_12h | actual_ICU_ outflow_12h | pred_ICU_net - change_12h | actual_ICU_net - change_12h | pred_ICU_ readmission | actual_ICU_ readmission | ICU_Bed_ _Demand |
|-------------------|------------------------------------|------------------------------|-------------------------|---------------------------|----------------------------|---------------------------------|-----------------------------------|--------------------------|----------------------------|---------------------|
| 2150/9/5 00:00 | 7 | 3 | 2 | 0 | 0 | 2 | 0 | 0 | 1 | 0 |
| 2150/9/5 12:00 | 11 | 3 | 2 | 1 | 3 | -1 | -2 | 0 | 0 | 2 |
| 2150/9/6 00:00 | 6 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 2150/9/6 12:00 | 7 | 3 | 2 | 1 | 3 | 0 | -2 | 1 | 0 | 1 |
| 2150/9/7 00:00 | 1 | 2 | 0 | 0 | 2 | -2 | -2 | 0 | 0 | 1 |
| 2150/9/7 12:00 | 9 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 2150/9/8 00:00 | 4 | 2 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 2150/9/8 12:00 | 8 | 3 | 3 | 2 | 2 | 1 | 0 | 0 | 0 | 1 |
| 2150/9/9 00:00 | 7 | 4 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 2 |
| 2150/9/9 00:00 | 4 | 4 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 3 |

Data Source



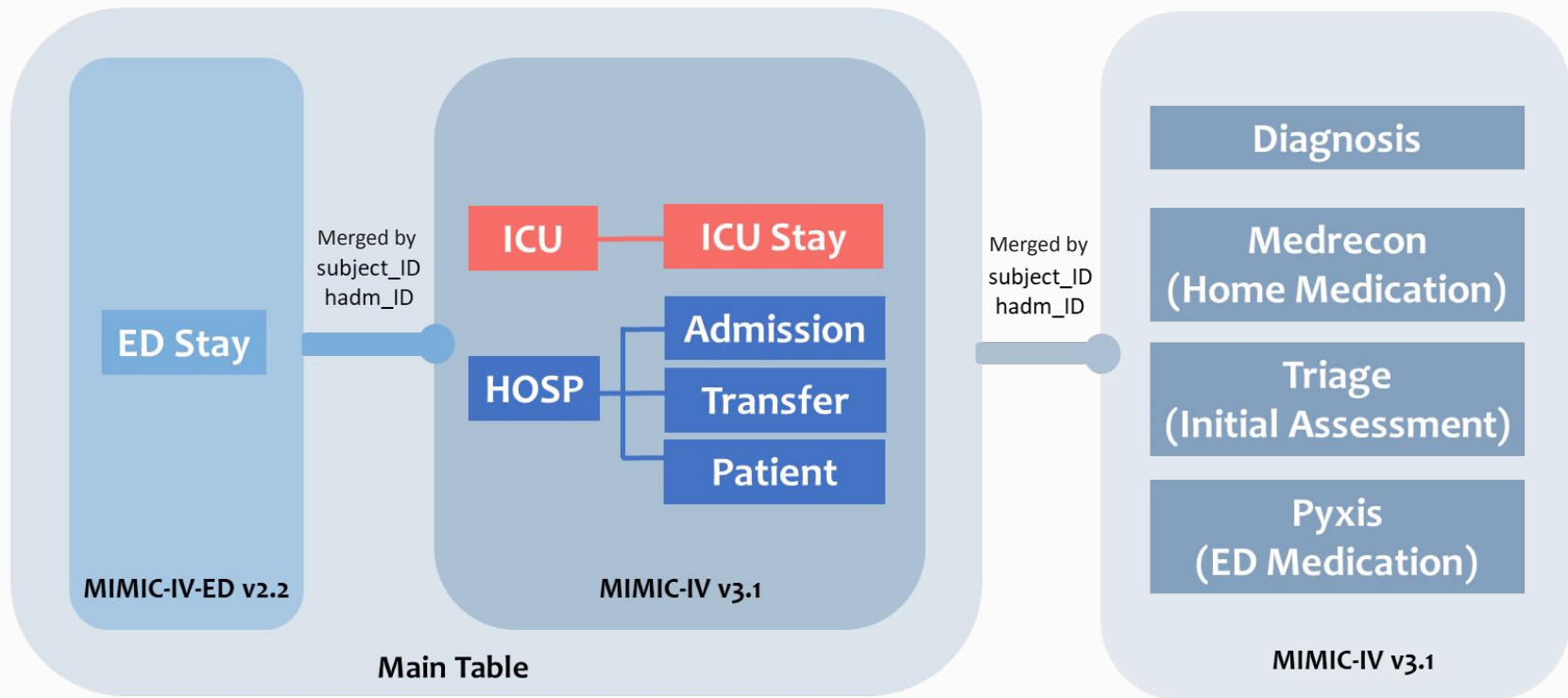
MIMIC-IV-ED v2.2

| Section | ED (Emergency Department) |
|---------------------|---|
| Original Data Name | Ed stays, diagnosis, triage (Initial Assessment), vital sign, medrecon (Home Medication), pyxis (ED Medication) |
| Key | subject_id (unique id for each patient), hadm_id (unique id for each hospital admission), Ed_stay (unique id for each ED visit) |
| Content Description | Emergency department visit data |

MIMIC-IV v3.1

| Section | HOSP (Hospitalization) | ICU (Intense Care Unit) |
|---------------------|---|--------------------------------|
| Original Data Name | Admissions, transfers, patient (Demography) | ICU Stays |
| Key | Subject_id, hadm_id | subject_id, hadm_id |
| Content Description | all hospitalization records, transfer records, and patients' informations | Intensive Care Unit visit data |

MIMIC-IV Data Merging



6. Current Status & Future Steps

Future Steps

