Two-Stage Patient Centric GNN for Early Prediction of Clinical Outcomes

Master's Degree in Artificial Intelligence and Robotics

Francesco Caracci (1915689)

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Clinical Problem

- Unrecognized Clinical Deterioration is a

  persistent challenge where subtle

  physiological changes go undetected, often

  leading to unplanned or emergency Intensive

  Care Unit (ICU) transfers

- Delayed recognition of high-risk patients is

  associated with increased mortality and

  worse clinical outcomes

- Accurate early prediction of ICU transfer

  and mortality is therefore a critical challenge

  in hospital care
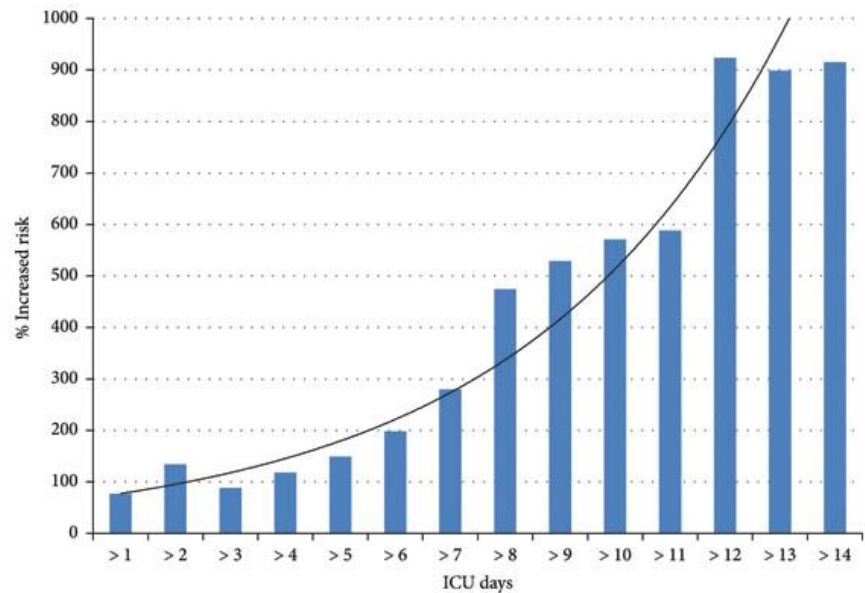
Limitations of Existing Approaches

Early Warning Scores:

- rule-based and threshold-driven

- limited expressiveness

Deep learning models on EHR:

- effective temporal modeling

- typically admission-centric

Missing information:

- patient longitudinal history

- population-level relationships

| Feature	EWS	Seq. Model	My model
Temporal modeling	✘	✔	✔
Patient History	✘	✘	✔
Population Context	✘	✘	✔

Why use graph structures?

- **Capture complex relationships** between patients (similar history, vitals, trajectories)

  → goes beyond isolated admissions

- **Encode contextual information** via edges and node neighborhoods

  → relational inductive bias improves modeling

- **Enable message passing**: each patient embedding is informed by neighbors

  → leads to better generalization on sparse or noisy EHR data
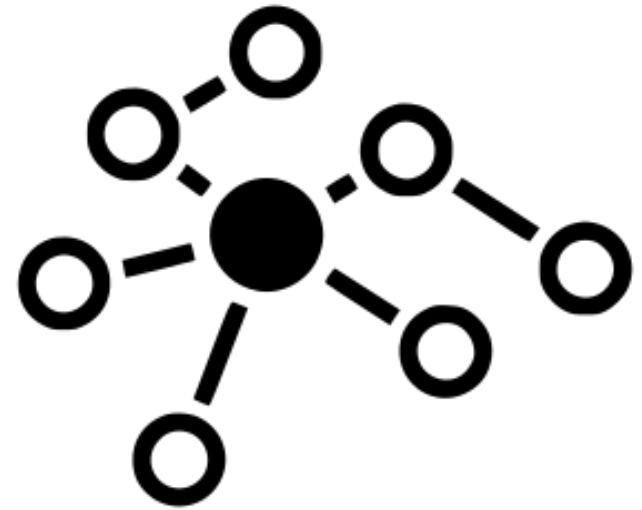
Proposed Methodology

- Two-stage predictive framework:

  ➢ **Stage 1:** Clinical State Estimator

  ➢ **Stage 2:** Patient-level GNN

- Jointly predicts:

  ➢ ICU transfer risk, delay and duration

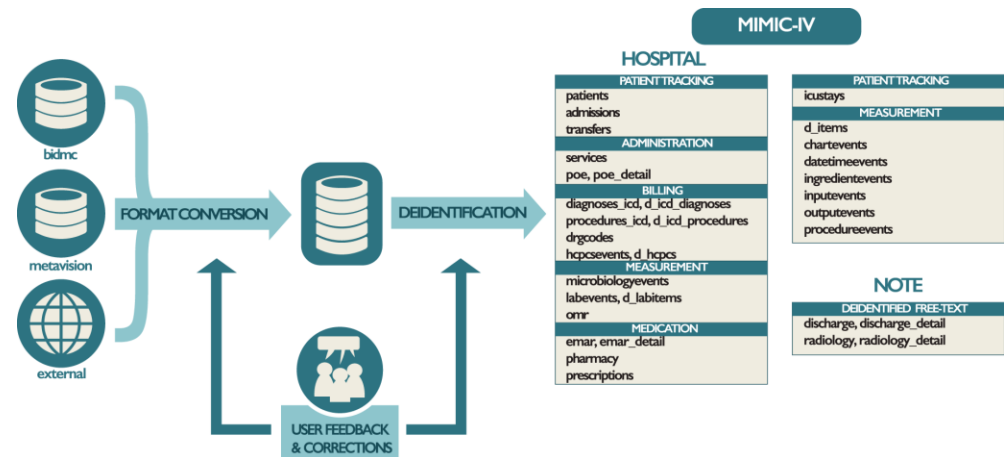 ➢ In-hospital mortality

  ➢ Discharge location
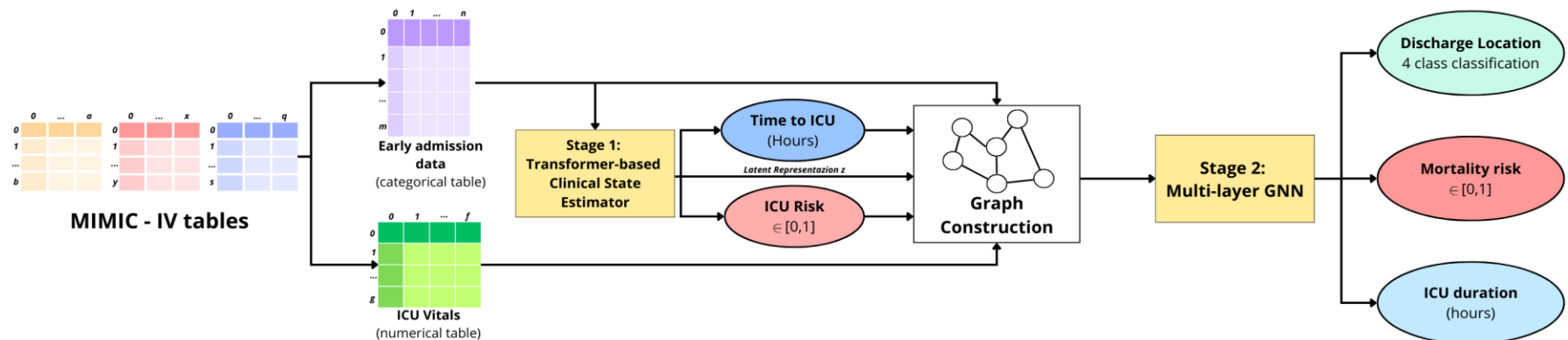
Dataset & Preprocessing

This research utilizes the **MIMIC-IV** database, which provides longitudinal hospital and ICU records at the patient level.

Raw electronic health records are transformed into structured admission-level representations designed to handle the irregularity of clinical data and support early prediction.

Features include demographics, vital signs, laboratory measurements, and high-level clinical descriptors, enabling the construction of longitudinal patient histories for downstream modeling.

Multi-Task Learning & Evaluation

Task 1: In-hospital Mortality (Classification)

Goal: Predict the likelihood of death during the stay.

Metrics: AUC & Accuracy

Task 2: ICU Length of Stay (Regression)

Goal: Estimate the number of hours the patient will spend in ICU.

Metrics: MAE & RMSE.

Task 3: Discharge Destination (Classification)

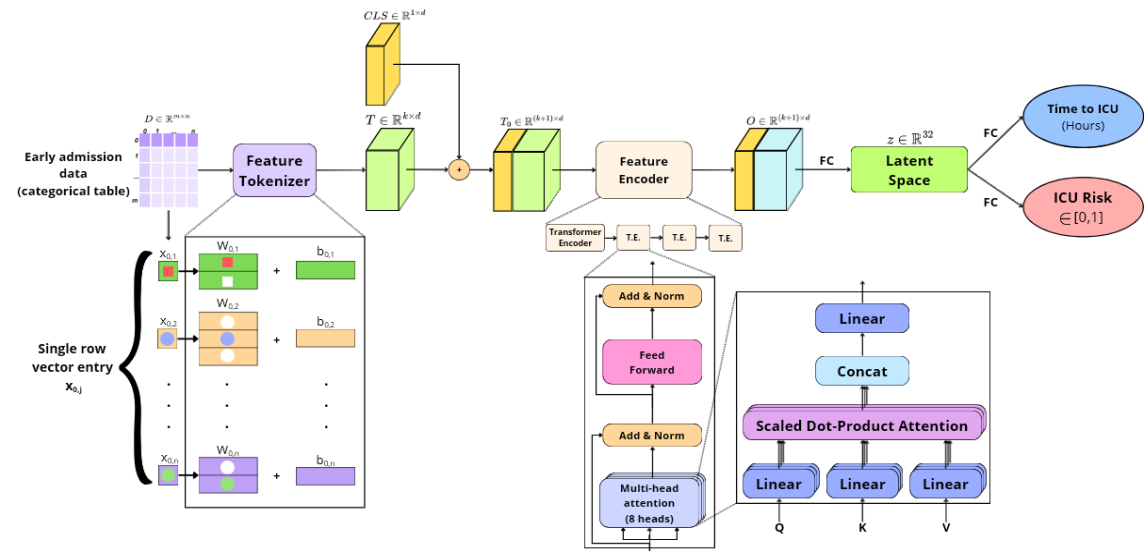**Goal:** Predict where the patient will go (Home, Skilled Nursing Facility, etc.).

Metrics: Accuracy & F1-Score

Stage 1: Clinical State Estimator

Admission features are

tokenized and passed through a

Transformer encoder.

Outputs:

- ICU transfer risk

- Time to ICU

- Latent embedding *z*

Two-Stage Patient Centric GNN for Early
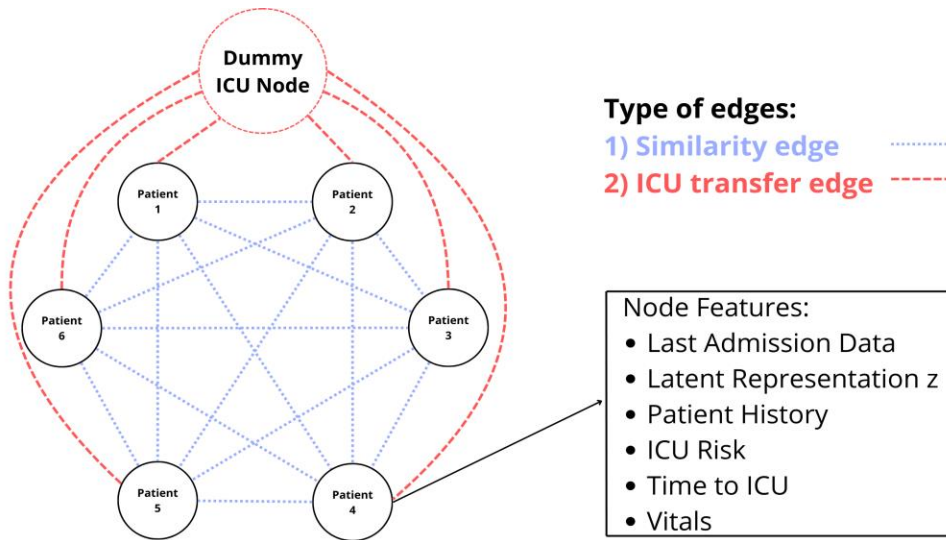Prediction
of Clinical Outcomes

Stage 1: Results

The FT-Transformer learns feature interactions and supports multi-task learning. It also outpereforms Logistic Regression, Random Forests and MLP.

Model	AUC$_{mort}$	Accuracy$_{mort}$	RMSE [h]	MAE [h]	RMSE / Mean	RMSE / σt
Linear Regression	---	---	90	45	2.61	0.89
Logistic Regression	0.751	0.701	---	---	---	---
Random Forest	0.756	0.707	92	45	2.67	0.91
MLP (single-task)	0.757	0.707	92	45	2.67	0.91
MLP (multi-task)	0.762	0.710	90	40	2.61	0.89
FT-Transformer (multi-task)	**0.770**	**0.710**	**92**	**35**	**2.67**	**0.91**

Patient-Centric Graph Modeling

Type of edges:
1) Similarity edge ··········
2) ICU transfer edge - - - -

Node Features:
• Last Admission Data
• Latent Representation z
• Patient History
• ICU Risk
• Time to ICU
• Vitals

- Each node represent a patient

- Node Features:last admission data, latent representetion, ICU Risk and delay, sequential admission embedddings (encoded with a GRU), ICU vitals (only for ICU patients)

- Two types of edges: similarity edges and ICU transfer edges

Stage 2: Hybrid GNN

- **Triple-Layer Stack:** A deep architecture integrating GCN, GATv2, and GraphSAGE to capture diverse relational features

- **Layer Specialization:**

  - ➤ **GCN:** Captures fundamental topological connectivity.

  - ➤ **GATv2:** Implements dynamic attention to weigh clinically relevant neighbors.

  - ➤ **GraphSAGE:** Ensures efficient and scalable feature sampling

- **Jumping Knowledge (JK) Mechanism:** an adaptive layer that aggregates representations from all previous levels of the stack. JK allows the model to use deep population context while preserving critical patient-specific details

Final Results

- Mortality prediction:

  ➢ AUC: **0.935**

  ➢ Accuracy: **0.959**

- ICU length of stay:

  ➢ MAE: **~38 hours**

  ➢ RMSE: **~59 hours**

- Discharge Destination:

  ➢ Accuracy: **0.757**

- Outperforms classical models and

  non-graph baselines

Work	Model	AUC_{mort}
Rocheteau et al. (2021)	LSTM	0.83
	LSTM+GNN	0.86
Harutyunyan et al. (2017)	LogReg	0.84
	LSTM	0.85
Bui et al. (2024)	XGBoost	0.87
	LSTM	0.83
van de Water et al. (2025)	GRU	0.87
Daphne et al. (2025)	Transformer+GNN	0.90
This Work	**Transformer+GNN**	**0.935**

Ablation Study

A focused ablation study was conducted to assess the contribution of key design choices in the proposed framework.

| Model	AUC$_{mort.}$	Accuracy$_{mort.}$	RMSE [h]	MAE [h]	Accuracy$_{disch.}$
Full Model	**0.935**	**0.959**	**59.27**	**38.61**	**0.757**
without patient history	0.912	0.928	63.12	39.63	0.754
GCN only	0.894	0.941	61.76	40.65	0.740
GATv2 only	0.901	0.951	60.98	39.06	0.740
GraphSAGE only	0.904	0.952	60.01	39.95	0.739
GCN + GATv2	0.896	59.86	59.86	38.87	0.739
GCN + GraphSAGE	0.898	0.927	60.38	39.12	0.741
GATv2 + GraphSAGE	0.904	0.959	59.92	38.84	0.738

Interpretability

Interpretability is essential in clinical decision-support systems.

The proposed framework provides insight at both the admission and patient levels, highlighting

clinically relevant features and meaningful patient similarities that contribute to the final predictions.

This improves transparency and supports a more trustworthy clinical adoption.
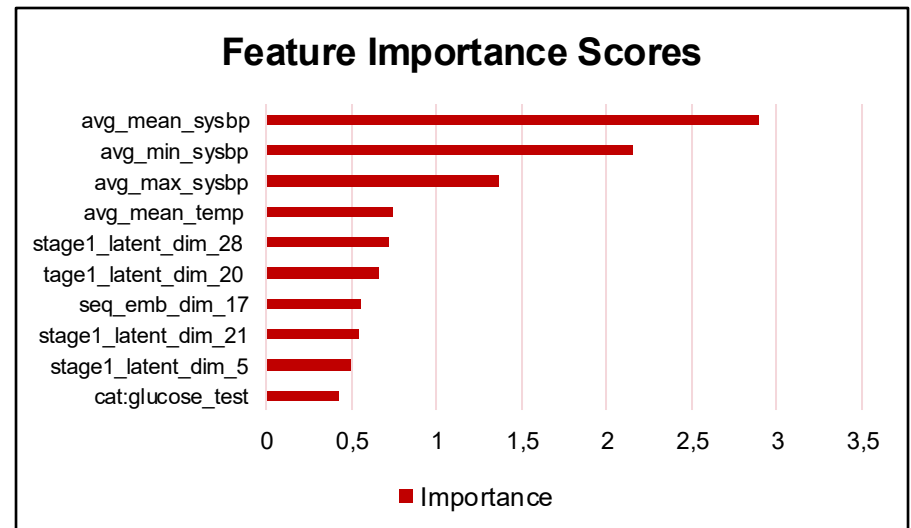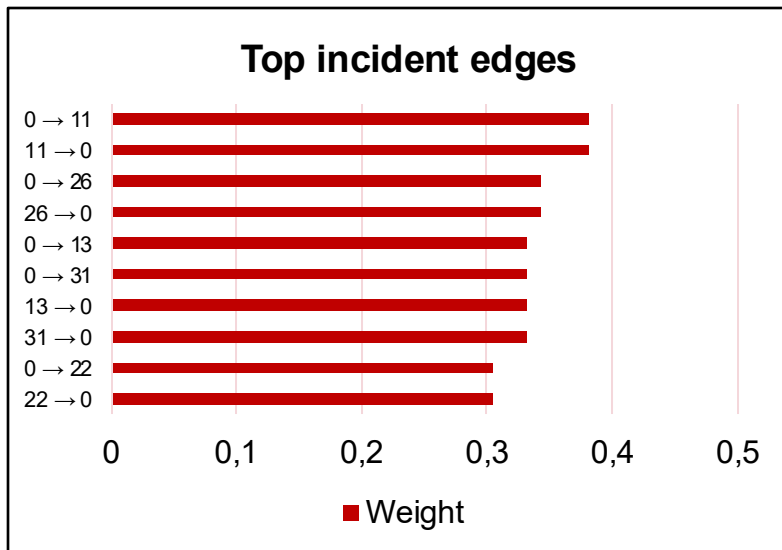
Conclusion

- This thesis presented a two-stage, patient-centric framework for early clinical outcome prediction, integrating admission-level temporal modeling with longitudinal and population-level graph reasoning.

- The proposed approach achieves strong performance across multiple tasks while remaining interpretable and clinically motivated.

- This work has contributed to a research article titled: **"An EHR Transformer-driven Feature Embedding Mechanism for GNNs Applied to ICU Outcome Prediction"** (E. Iacobelli, E. Branca, F. Caracci, M. G. Bocci, C. Napoli), which has passed the first review phase of the **AAAI-26 conference** submission process.

Thank You for listening!