Predicting ICU Length of Stay: A Graph Learning-based Explainable AI Approach

Regular Paper

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Introduction

Intensive care units (ICUs) play a vital role in providing life-saving capabilities to patients with severe diseases, comorbidities, and life-threatening conditions. However, the operation of ICUs comes with a significant resource burden in terms of staffing and equipment utilization, including ventilators and surgical equipment. The cost of an ICU bed is four times higher than that of a general ward, exceeding $4,000 per day (Canadian Institute for Health Information 2016; Kaier et al. 2020). In the United States, ICU costs accounted for 13.0% of hospital costs and 4.1% of national health expenditures in 2010, with a continuous rise over the past decade (Halpern and Pastores 2010). Studies in India have shown that a third of hospital budgets are spent on ICUs, and a third of inpatient costs can be attributed to ICU stays (Multz et al. 1998; Shweta et al. 2013). These costs have substantial implications for hospital budgets and national health expenditures, underscoring the need to optimize ICU expenses while maintaining high-quality patient care.

Accurately predicting the length of stay (LoS) for ICU patients, particularly those at risk or with severe complications, is crucial for hospitals. LoS is not only used to measure treatment effectiveness but also to schedule resources and make staffing decisions. Previous research has revealed that precise prediction of discharge times for current ICU patients can enable more efficient allocation of ICU resources (Romano et al. 2014). Additionally, it is also demonstrated that LoS for ICU patients, especially those at risk with severe complications, is a key metric for managing ICU resources and evaluating the quality of care provided (Oh et al. 2018; Rosen et al. 1999). Thus, accurate LoS predictions can facilitate improved resource allocation and enhanced discharge planning.

In this paper, we emphasize the importance of providing concise explanations alongside accurate predictions in ICU settings. Building upon the extension of Cognitive Load Theory (CLT) to clinical environments (Szulewski et al. 2021), our goal is to alleviate the cognitive burden associated with utilizing electronic medical data and decision support systems through explanatory information. In clinical settings, previous literature has shown that effective information filtering and relationship extraction can enhance task completion speed and reduce cognitive errors (Ahmed et al. 2011). Therefore, we believe identifying critical inter-modal relationships indicative of abnormal disease progression can significantly reduce the mental effort required to understand a patient's status and predicted outcome, which enables healthcare professionals to provide better care in time sensitive ICU settings. To achieve this, we introduce a novel approach based on deep graph learning that takes inspiration from graph structure learning to accurately predict ICU LoS while generating relation graphs that highlight the key clinical features patients as well as their interactions of for explanation and interpretation purposes.

This proposed graph learning approach contributes to the relevant literature on explainable prediction of health outcomes by explicitly modeling the interactions between clinical features and summarizing such learned interactions into relational graphs. The relational graphs constructed are not only utilized to predict ICU LoS accurately but also facilitate a deeper comprehension of the interplays between clinical features, going beyond the feature-based explanations and interpretations provided by current XAI approaches. We validate our approach using the Medical Information Mart for Intensive Care III (MIMIC-III), a large longitudinal panel of patient visits to a major teaching hospital's ICU over a twelve-year period. While our primary focus is on ICU LoS prediction, our approach can be easily generalized to predict and interpret other health outcomes, such as mortality, readmission risk, and duration of inpatient (hospital) stays.

Methodology

In this section, we provide an overview of the data utilized as well as a description of the graph learning model.

Data

We utilized data from the MIMIC III database, which comprises de-identified health data from over 61,000 ICU admissions at the Beth Israel Deaconess Medical Center between 2001 and 2012 [26]. From this dataset, we selected 22,000 encounters that lasted longer than two days and represented patients' initial visits. A summary of the descriptive statistics of our data is provided in Table 1.

Variable Name	Description and Unit of Measure	Distribution
Binary Output Variables		
7-day discharge	Binary indicator of ICU patients discharged after the seventh day	28.79%
Selected Input Variables		
Vital Signs		
HeartRate	Heart rate of the patient measured in beats per minute	94.06 (25.22)
SysBP	Systolic blood pressure of the patient in mmHg	120.21(20.42)
DiasBP	Diastolic blood pressure of the patient in mmHg	60.35 (12.78)
MeanBP	Mean blood arterial pressure of the patient in mmHg	78.76 (14.02)
RespRate	Patient respiration rate in breaths per minute	19.36 (5.20)
TempC	Body temperature of the patient in degree Celsius	37.02 (0.83)
SpO2	Fraction of oxygen-saturated hemoglobin relative to total hemoglobin in the blood	97.10 (2.86)
Glucose	Concentration of glucose present in the blood of patients in mg/dl	141.60(55.82)
Administrative Variables		
Age	Patient age in years	55.47(27.59)
Gender$_F$	Binary (1 = patient is female)	44.10%
Ins Medicare	Binary (1 = patient insurance is Medicare)	47.65%
Ins Medicaid	Binary (1 = patient insurance is Medicaid)	9.61%
Adm Elective	Binary (1 = patient from elective admission)	12.35%

Standard deviations are shown in parentheses.

Table 1. Descriptive Statistics

Graph Learning Model

We propose a novel graph learning-based model drawing inspiration from the burgeoning field of graph structure learning. This model aims to predict ICU LoS by creating patient-level relational graphs. These graphs illustrate not just the importance of individual (patient-level) features but also the interactions between features and their impact on the prediction outcome. A visual representation of our proposed model is displayed in Figure 2.

In the first step, each patient's input features are transformed into a one-dimensional vector within a unified feature space using various projection layers. These projection layers are customized for specific types of input features, utilizing LSTM units to process patient vital signs, and fully connected neural layers for the remaining patient (input) features. In step 2, a fully connected directed graph is constructed for each patient based on the projected input features. In such a graph, each node corresponds to a specific input feature, with the associated projection encapsulated as the node feature.

In step 3, we leverage a graph attention network (GAT) to refine the node features by incorporating relevant information from neighboring nodes and to assign weights to edges within the graph, indicating their importance in the prediction process. GAT is a specialized type of message-passing neural network tailored for graph-structured data that utilizes attention mechanisms to selectively focus on and aggregate information from adjacent nodes (Veličković et al. 2017). The features of each node in the GAT are updated with a weighted sum of the features of its neighboring nodes. These weights are dynamically determined by an attention mechanism, which assesses the relevance of each neighbor in relation to the feature vector of the focal node. The attention values generated by the GAT serve two key functions. First, they influence the weighting scheme for the messaging process, enabling more nuanced data integration. Second, they provide a one-to-one correspondence with the graph edges which enables us to interpret attention values as indicators of the importance of each edge in the overall information flow.

Next, in step 4, an attention-based read-out mechanism is utilized to distill the graph into a one-dimensional representation. This process involves creating a weighted sum of the node features that have been updated through the GAT. The weights for this sum are determined by a separate attention mechanism which evaluates the relevance of each updated node in relation to the overall prediction task. These attention values not only dictate the weighted sum but also serve as indicators of the importance of each node's enriched features in making accurate predictions.

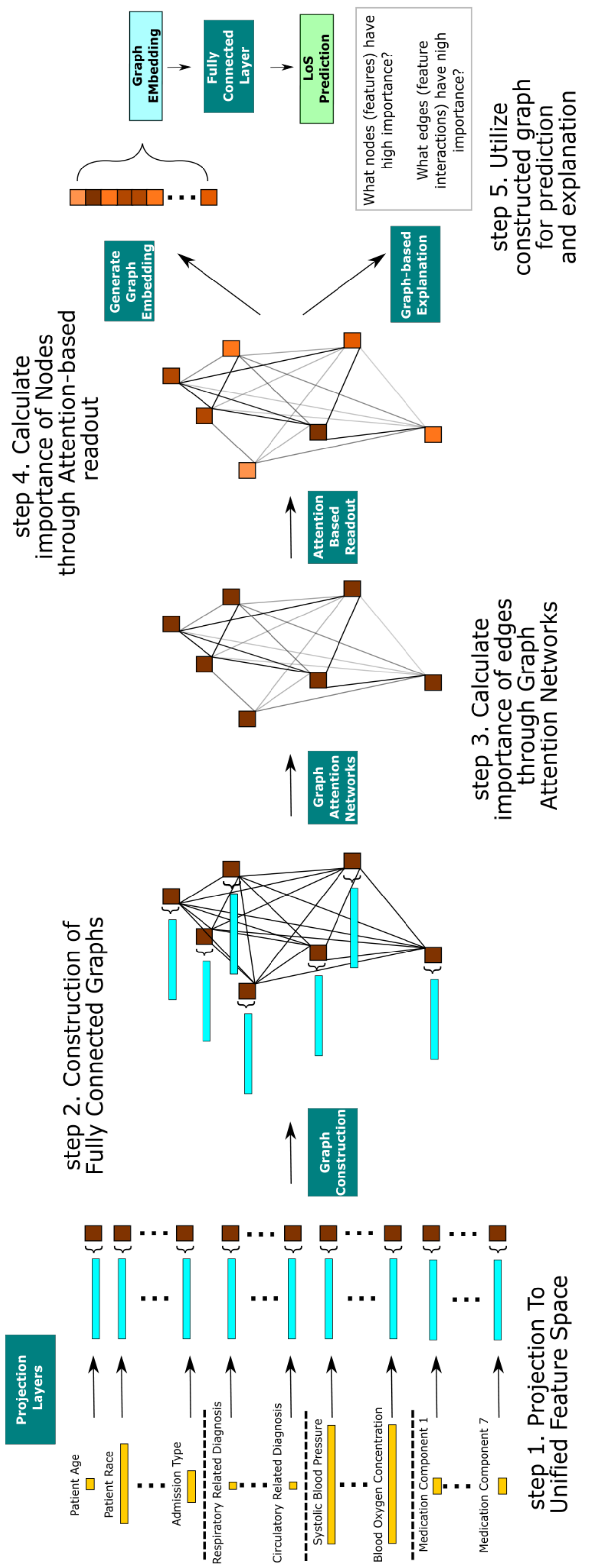

Figure 1. Joint Graph Structure and Representation Learning Network

Finally, in step 5, the condensed graph-level representation—obtained from the attention-based read-out in step 4—is processed by a sequence of fully connected neural layers to generate the final prediction for ICU LoS. Simultaneously, the attention values from steps 3 and 4 naturally construct a patient-specific relational graph. This graph not only encapsulates the importance of individual features but also illuminates their intricate interactions in contributing to the ICU LoS prediction of each patient.

Results

In this section, we present results on the predictive performance of the graph learning model in comparison against alternative prediction methods and demonstrate that the insights provided by the generated relational graphs are medically relevant.

Predictive Performance

Table 2 provides a comparison of the performance of various machine learning models against the proposed graph learning model in predicting ICU LoS as a binary task of predicting ICU discharge within a 7-day timeframe. The values presented are the average, with standard deviation in parenthesis, across 10 repetitions using an 8/1/1 split between training, validation, and test.

	Method	Accuracy	AUROC	AUPRC	F1-Score
1	Graph Learning Model	**0.767 (0.003)**	**0.824 (0.002)**	**0.899 (0.003)**	0.829 (0.003)
4	XGBoost	0.762 (0.004)	0.810 (0.006)	0.890 (0.005)	0.831 (0.003)
5	Random Forest	0.755 (0.05)	0.803 (0.007)	0.880 (0.005)	**0.836 (0.003)**
6	Logistic Regression	0.732 (0.005)	0.729 (0.007)	0.826 (0.007)	0.818 (0.004)

Standard deviations are shown in parentheses.

Table 2. Predictive Performance Comparison of Different Models

The results indicate that the graph learning model outperforms alternative machine learning methods by a significant margin. Specifically, in the test set, the graph learning network achieves the best accuracy, AUROC, and AUPRC across the four prediction methods examined, with values of 0.767, 0.824, 0.899, respectively stands at 0.771, 0.772, and 0.772, respectively. The random forest model stands out with the highest F1 score of 0.836, but it is crucial to note that in our data only about 30% of the patients stay in the ICU for more than seven days, making this an imbalanced prediction task. Hence, metrics such as AUROC and AUPRC are especially important since they are less sensitive to class imbalance compared to model accuracy or F1 scores, which can be skewed by the choice of classification threshold.

The notable improvement in the predictive performance of our graph learning model compared to traditional machine learning models validates the efficacy of our approach. It demonstrates that the graph learning model can offer enhanced explanatory capabilities without compromising predictive accuracy.

Explanation Capability

We first show how the graph learning model can explain its predictions by examining the constructed relational graph for a specific patient. Subsequently, we scrutinize the essential features and interactions identified by our graph learning model in the prediction process across the entire patient population. Finally, we confirm that the feature interactions highlighted by the model are medically relevant, proving that the model's explanations can be trusted in a healthcare setting.

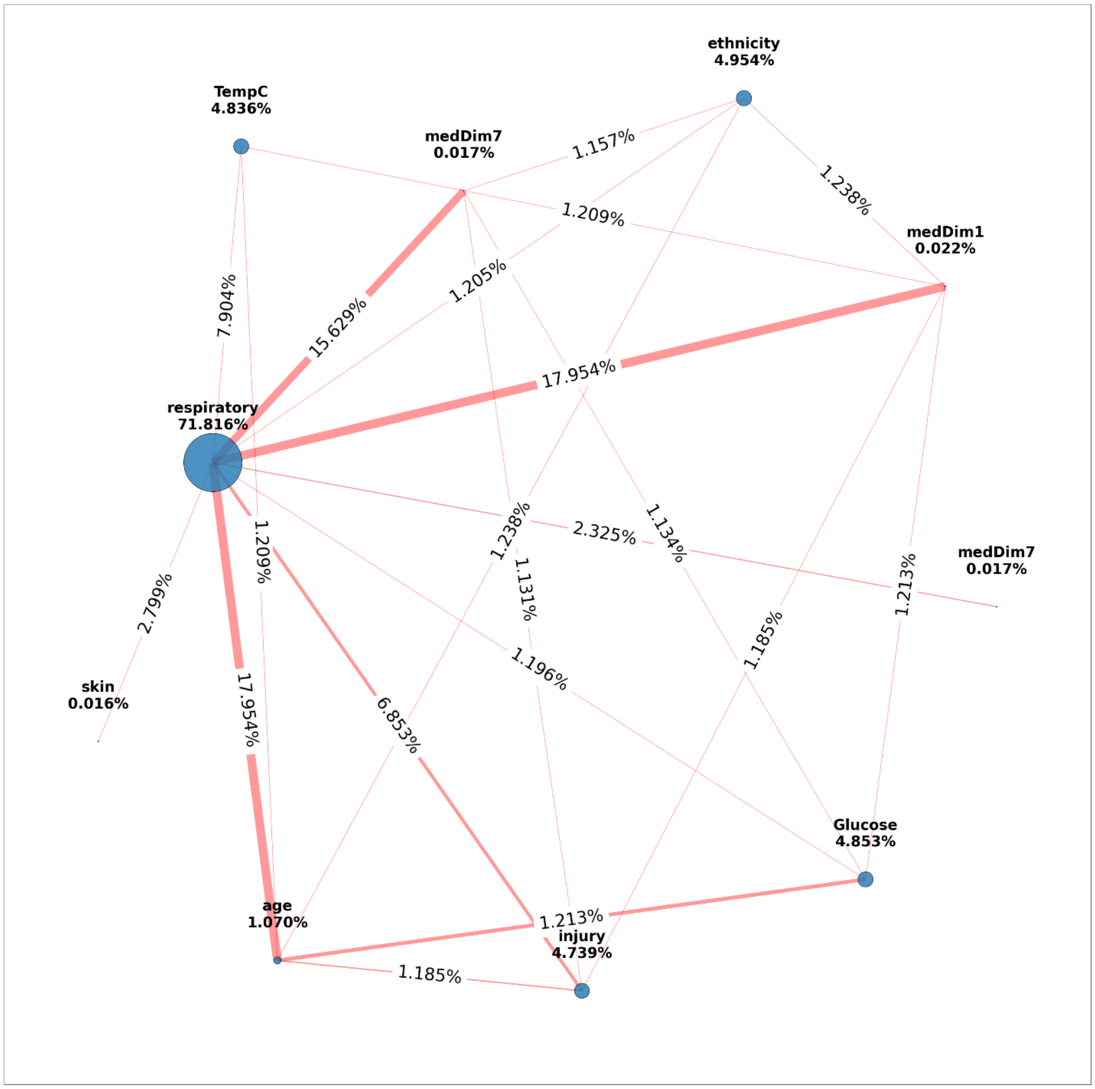

Figure 2. Example Personalized Sparse Relational Graph from Graph Learning Model

Figure 2 shows a patient-level graph created by our graph learning model for a 46-year-old male admitted to the surgical ICU via the emergency department. The model accurately predicted that his ICU stay would last over seven days. Node size and edge width in the graph indicate their importance in predicting length of stay (LoS). For example, the respiratory diagnosis node was most prominent, capturing 71.81% of the attention. However, significant parts of this attention—about 18% each—are linked to interactions with the patient's age and medication components, emphasizing that the respiratory diagnosis is not important in isolation but in conjunction with other features. Other factors like glucose level, body temperature, and injury diagnosis also play key roles, and their impact is shaped by interactions with additional features. We believe such relational graphs can be easily interpreted by physicians in understanding the key drivers of a patient's ICU LoS.

Table 3 identifies the top five features and feature interactions based on average node and edge attention across the patient population. Respiratory diagnosis stands out with the highest average node attention at 17.96%, indicating that this feature and its interactions contribute to nearly 18% of the relevant information for LoS predictions. The interaction between mental health disorder and marital status has the highest average edge attention of 0.00067, and closer inspection suggests that single patients with mental health issues are more likely to have longer ICU stays. While these average edge attention values may seem small, they become meaningful when considered at the individual patient level where only a few edges have significant attention values (as shown in Figure 2), demonstrating the model's ability to capture patient-specific complexities.

Feature Name	***Average Node Attention***	***Interaction***	***Average Edge Attention***
Respiratory system related diagnosis	0.179	Mental disorders ***X*** Marriage status	0.00067
Heart rate	0.107	Patient age ***X*** Mean BP	0.00065
ICU type	0.063	Diseases of the digestive system ***X*** Infectious and parasitic diseases	0.00064
Symptoms, signs, and ill-defined conditions	0.056	Medication component 3 ***X*** Respiration rate	0.00064
Diagnosis of injuries and poisoning	0.054	Pregnancy complications ***X*** Hospital admission type	0.00063

Table 3. Top Features and Interactions from Graph Learning Model

Lastly, we assess the medical relevance of the feature interactions pinpointed by our graph learning model. In Table 4, we cross-reference these interactions with existing medical research to validate their clinical significance. Notably, four out of the top five interactions identified align with current medical literature, confirming the clinical validity of the explanations provided..

Interaction	***Medical Concepts***
Mental disorders ***X*** Marriage status	Compared to married individuals, single or divorced individuals experience poorer mental well-being, especially in men(Grundström et al. 2021).
Patient age ***X*** Mean BP	Advanced age is associated with an increase in blood pressure (Singh et al. 2022). Management of patient blood pressure should take into consideration of their age (Yu et al. 2023).
Diseases of the digestive system ***X*** Infectious and parasitic diseases	Abdominal infections are frequent causes of sepsis and septic shock in the intensive care unit (ICU) and are associated with adverse outcomes (De Waele et al. 2014). The presence of specific gastrointestinal microbial pathogens at ICU admission is associated with an increased risk for death (Freedberg et al. 2018).
Pregnancy complications ***X*** Hospital admission type	Acute complications of pregnancy are risk factors for referral to the ICU and may increase risk for unexpected outcomes among mothers and neonates (Lin et al. 2019).

Table 4. Support from Medical Literature

For example, the highlighted edge between diagnosis under the category of *pregnancy complications* and hospital admission type suggests that the duration of an ICU stay due to *pregnancy complications* might be significantly influenced by the route through which the patient was admitted to the hospital. Supporting this proposition, studies in the existing medical literature have pointed out that acute complications arising during pregnancies, such as amniotic fluid embolism or acute fatty liver, intensify the risks for both the mother and the neonate (Lin et al. 2019) . Given the urgency and severity typically associated with admissions through high-acuity pathways, such as emergency rooms, it is reasonable to deduce that patients with *pregnancy complications* admitted through these routes are at increased risk—they are most likely suffering from the acute conditions documented in the literature. As such, these patients would demand more rigorous clinical monitoring and intervention to ensure optimal health outcomes.

Conclusion

The primary objective of this study is to devise accurate and interpretable models tailored for forecasting ICU LoS that provide practical, data-derived insights for healthcare professionals. We contend that such models can effectively alleviate the cognitive load associated with utilizing electronic medical data and decision support systems in ICU environments, ultimately augmenting the caliber of care extended. We propose a novel graph learning model that achieve precise ICU LoS predictions while concurrently fabricating relational graphs spotlighting pivotal patient clinical features and their interactions to facilitate explanations and interpretations. Although our primary focus centers on predicting ICU LoS, our methodology seamlessly extends to prognosticating and interpreting a spectrum of other health outcomes, encompassing mortality, readmission risk, and duration of inpatient (hospital) stays.

Our initial results indicate that the graph learning model surpasses existing models in predictive accuracy and identifies key feature interactions that significantly influence outcomes. We cross-reference them with existing medical literature to validate the medical relevance of highlighted interactions and confirm that a majority of these interactions are medically supported, lending clinical validity to our explanations. We believe the proposed graph learning model can facilitate more intuitive understanding for healthcare professionals by highlighting medically relevant, key feature interactions.

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