Prediction of Hospital Length of Stay for Planned Admissions Using OMOP CDM

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Background

Accurate prediction of patient hospital length of stay (LOS) is essential in healthcare systems for optimal patient care provision, healthcare planning, and effective hospital resource management (1-3). LOS has a direct impact on various aspects of hospital operations and healthcare service delivery. Consequently, LOS serves as a crucial indicator of healthcare utilization efficiency, alongside cost considerations. However, LOS prediction models are often compromised by limited covariates and heterogeneity in healthcare data, hospital systems, and patient populations. (4-7) These issues can be addressed by using the Observational Medical Outcomes Partnership Common Data Model (OMOP CDM), which is a standardized framework that streamlines and harmonizes healthcare data from diverse sources. In this study, we developed and validated machine learning-based models for predicting hospital LOS using OMOP CDM.

Methods

Retrospective patient-level prediction (PLP) models were developed using electronic health record (EHR) data from the Seoul National University Bundang Hospital (SNUBH) in South Korea, which were converted to the OMOP CDM (version 5.3). The database contains the EHR data of 1,903,603 million patients (40,723,280 admissions) accumulated from 2003 to 2020. The study included 137,123 patient entry events from January 2016 to December 2020, each with at least one recorded condition occurrence, and one inpatient visit lasting between two and 30 days. Each visit was a planned admission with no deaths during hospitalization. Two cohorts were extracted from this data using an ATLAS instance: planned admissions and planned admissions with surgical operations. Covariates from person, condition occurrence, medication, observation, measurement, procedure, death, and visit occurrence tables were included in the analysis. These covariates were generated and extracted using an open-source package (Feature extraction, Version 3.0.1) and R software (version 4.0.5). Additionally, custom covariates were incorporated including time, day of the week, holidays, diagnosis at hospital admission and number of days to the surgery from the admission, day of the week operation, operations performed, vital signs, and anthropometric measurements. Logistic regression, coupled with

Lasso regularization was employed as a classifier to eliminate redundant from the dataset prior to model training. The primary outcome was hospitalization with a length of stay of seven days or more. Logistic regression (LR), random forest (RF), extreme gradient boosting (XGB), light gradient boosting (LGB), gradient boosting (GB) and multilayer perceptron (MLP) algorithms for classification were used in this study. The performance of the models was evaluated based on metrics such as the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, positive predictive value, and negative predictive value. SHapley Additive exPlanations (SHAP) analysis and calibration plots were utilized to measure feature importance and assess the reliability of the prediction models, respectively.

Results

Of 137,123 planned hospital admissions, 80,180 were surgery admissions. After preprocessing, we identified 129,938 planned admissions, of which 75,220 were for surgeries. The mean age of planned admissions was 58.5 years, 45.3% of patients were men, and 33% were LOS >= seven days, whereas the surgical cohort had a mean age of 56.5 years, 40.4% of patients were men, and 37.7% were LOS >= seven days. (Table 1). The Extreme Gradient Boosting (XGB) model achieved the best performance in planned admissions, with an AUROC of 0.891 and an area under the precision-recall curve (AUPRC) of 0.819. Among the surgical patients, the Light Gradient Boosting (LGB) had the highest performance, with an AUROC of 0.948 and an AUPRC of 0.856 (Table 2). The most important features contributing to the predictive performance of the models were operation performed, admitting unit, age, Charlson index - Romano adaptation and the count of outpatient visits in the past six months for planned admissions. For surgical patients, the most contributing factors were time to surgery from hospital admission, Charlson index - Romano adaptation, admitting unit and age. The overall models showed good calibration in both cohorts, except for the LR model.

Table 1. Baseline characteristics of planned admissions and surgical patients.

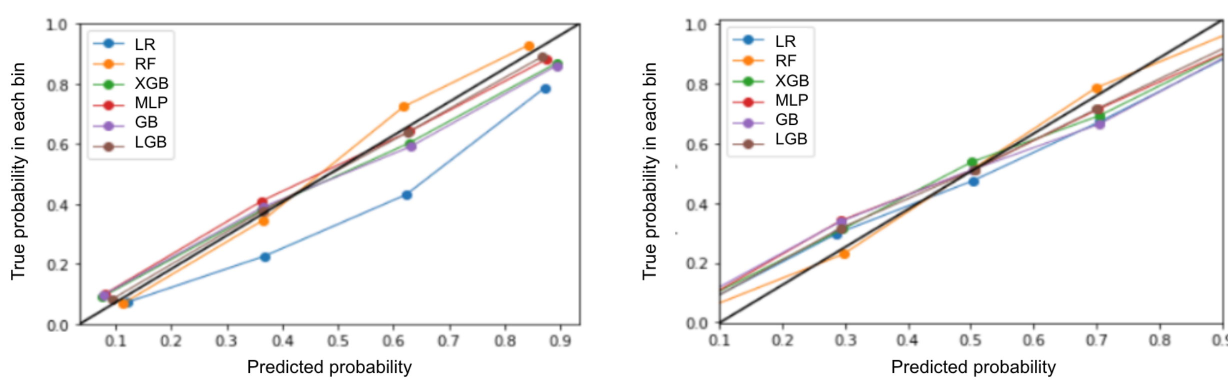
Cohorts	**Chacteristics**	**LOS< 7 (N = 95,499)**	**LOS>=7 (N = 34,439)**	**Overall (N = 129,938)**
Planned admissions	Age (years)	57.5 (15.5)	60.9 (15.0)	58.4 (15.4)
	Sex, men (%)	42,117 (44.1%)	16,762 (48.7%)	58,879 (45.3%)
	Operation performed			
	Yes	45,776 (47.6%)	23,850 (69.3%)	69,626 (53.6%)
	No	49,723 (52.1%)	10,589 (30.7%)	60,312 (46.4%)
	Severity score			
	CHADS2VASc	1.3 (1.1)	1.4 (1.2)	1.3 (1.1)
	CHADS2	0.6 (1.0)	0.7 (1.1)	0.6 (1.0)
	DCSI	0.5 (1.2)	0.6 (1.4)	0.6 (1.3)
	Charlson index - Romano adaptation	2.1 (2.5)	2.2 (2.2)	2.11 (2.4)
	Chacteristics	**LOS< 7 (N = 46,831)**	**LOS>=7 (N = 28,389)**	**Overall (N = 75,220)**
planned admissions with surgical operations	Age (years)	53.7 (15.6)	61.0 (14.2)	56.6 (15.5)
	Sex, men (%)	17,483 (37.3%)	12,919 (45.5%)	30,402 (40.4%)
	Time to surgery from admission			
	<= 5 days	46,803 (99.9%)	24,797 (87.3%)	71,600 (95.2%)
	> 5 days	28 (0.1%)	3,592 (12.7%)	3,620 (4.8%)
	Severity score			
	CHADS2VASc	1.2 (1.0)	1.4 (1.1)	1.3 (1.0)
	CHADS2	0.4 (0.8)	0.7 (1.0)	0.5 (0.9)
	DCSI	0.3 (1.0)	0.5 (1.2)	0.4 (1.1)
	Charlson index - Romano adaptation	1.3 (1.8)	2.1 (2.1)	1.6 (2.0)

Data are presented as number (%) or mean (SD), unless otherwise specified. LoS, Length of Stay; DCSI, Diabetes Complications Severity Index

Table 2. Performance of the prediction models in planned admissions and surgical patients.

Cohort	Models	AUROC	AUPRC	Sensitivity	Specificity	PPV	NPV
Planned admissions	**LR**	0.853	0.744	0.771	0.785	0.642	0.873
	RF	0.881	0.802	0.604	0.922	0.794	0.824
	XGB	0.891	0.819	0.686	0.896	0.768	0.852
	GB	0.888	0.811	0.681	0.894	0.763	0.849
	LGB	0.889	0.816	0.661	0.906	0.778	0.843
	MLP	0.882	0.804	0.635	0.910	0.778	0.833
planned admissions with surgical operations	**LR**	0.935	0.836	0.88	0.853	0.865	0.93
	RF	0.931	0.841	0.864	0.839	0.866	0.92
	XGB	0.947	0.854	0.889	0.866	0.879	0.942
	GB	0.943	0.852	0.877	0.853	0.876	0.937
	LGB	0.948	0.856	0.884	0.861	0.88	0.943
	MLP	0.944	0.849	0.885	0.861	0.875	0.938

Note: LR, Logistic Regression; RF, Random Forest; XGB, Extreme Gradient Boosting; LGB, Light Gradient Boosting; MLP, Multi-layer perceptron; AUROC, Area UndeCar the Receiver Operating Curve; PPV, Positive Predictive Value; NPV, Negative Predictive Value; AUPRC, Area Under the Precision Recall Curve



a. Planned admissions

b. surgical patients

Figure 1. Calibration of models for prediction of hospital length of stay in planned admissions and surgical patients.

Conclusion

We demonstrated the use of the OMOP CDM to predict LOS for both planned and surgery admissions. Predictors such as surgical operations, admitting specialty, age have been identified as potential contributors, while time to surgery, severity score, admitting specialty are predictive in surgery admissions. These models could provide insights and strategies for optimizing resource utilization across various healthcare facilities that implement OMOP CDM, potentially leading to reduced surgical mortality rates and improved overall operational efficiency. Additional research necessary to validate the models' performance across different institutions is currently underway, using external validations within the OHDSI network community.

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