ICHOM measures to improve predictive model performance: length of stay following elective spine surgery.

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BACKGROUND

Prolonged length of hospital stay (length of stay [LOS]) following elective spine surgery can increase the cost of care.

Waiting until after surgery to identify patients at high risk of prolonged LOS limits the window of opportunity to intervene and therefore the utility of many predictive models.

Augmenting LOS predictive models with Patient Reported Outcome Measures gathered before surgery could allow for earlier and more effective interventions such as pre-surgical physical therapy ("prehab"), optimizing the home environment, and supplemental education to set appropriate discharge and home care expectations with the patients and their families.

OBJECTIVE

To determine if adding baseline PROMs to LOS predictive models improves the models' predictive accuracy.

METHODS

Patient Population: From June 2017 through October 2019 St. Luke's Spine Program collected ICHOM measures from 7224 patients (76.6% Lumbar, 23.4% Cervical). Of these, 1381 underwent elective spinal surgery (1023 Lumbar, 358 Cervical) performed by 7 surgeons at 2 hospitals.

Primary Outcome: The primary outcome variable was LOS during index procedure hospitalization.

PREDICTIVE MODEL

Predictor Variables: Two separate datasets were created for the1381 surgical episodes of care (EOCs).

Dataset 1: EHR = EHR-derived demographic, medical, and treatment data
Dataset 2: EHR+PRO = Dataset 1 plus baseline PRO data from ICHOM measures

Data Analysis: Both datasets were analyzed with statistical (Best Subset Linear Regression) and machine learning (Random Forest Regression) algorithms. Ten-fold cross validation was used to mitigate the risk of overfitting. For both analyses, the proportion of variation in the outcome variable (LOS) explained by each of the predictor datasets (EHR and EHR+PRO) was expressed as R^2.

RESULTS

Primary Outcome: Average LOS for the 1381 surgical EOCs = 2.62 ± 1.68 days (Mean ± Std Dev), range <1 to 17 days.

Comparing predictive model performance with and without PROs:

Both statistical and machine learning algorithms performed better when Patient Reported Outcomes (PROs) were added to demographic, medical, and treatment data from the electronic health record (EHR) [**Table 1**].

Table 1

Regression Analysis for Length of Stay

	Predictor Variable Dataset	
Regression Model	EHR	EHR+PRO
Best Subset R^2	0.21	0.25
Random Forest R^2	0.18	0.29

Influence of individual predictor variable :

PRO factors that improved model performance included (descending order): PROMIS-10 Global Physical Component Score, Oswestry- and Neck-Disability Indecies, PROMIS-10 Global Mental Component Score, self-reported anxiety or depression, self-reported help at home, and self-reported opiate use frequency. [**Table 2**].

Table 2

Best Subset Linear Regression for LOS: Predictor Variables Selected by Dataset

	Predictor Variable	*P-value*
EHR	Procedure Time	<0.0001
	Invasiveness Score	<0.0001
	Age	<0.0001
	Body Mass Index	0.012
	Spinal Region	<0.0001

Best Subset Linear Regression for LOS: Predictor Variables Selected by Dataset

	Predictor Variable	*P-value*
EHR+PRO	Procedure Time	<0.0001
	Invasiveness Score	<0.0001
	Age	<0.0001
	Opiate Use	0.0722
	Help available at home	0.00314
	Anxiety or Depression	0.06044
	Spinal Region	<0.0001
	PROMIS-10 Physical Score	<0.0001

CONCLUSION

- When using statistical or machine learning analytics to predict LOS following elective spine surgery, adding patient-reported data included in the ICHOM measures improved model performance.
- A potential limitation of our predictive models is that they relied upon preoperative baseline factors and treatment (surgical) variables but excluded surgical complications and other hospital acquired conditions. Inclusion of these factors may further improve model performance but may not improve model utility for targeting resources and interventions designed to reduce LOS.
- Future related work will include prospective validation of the models followed by point-of-care deployment for individual patient real-time risk-stratification and resource allocation.