Finalist ID: BP-HSR-01

Tan Tock Seng Hospital
NHG Health

Predicting Rehabilitation Length of Stay in Singapore Tertiary Rehab: Insights from Machine Learning Models

Yong Siang Ong[1], Yong Sheng Heng[1], Ye Li[1], Xiaojin Zhang[1], Kee Hao Leo[1], Kenneth Jun Hong Ngoh[2], Karen Sui Geok Chua[2,3,4]

[1] Management Information Department, Office of Clinical Epidemiology, Analytics & kNowledge (OCEAN), Tan Tock Seng Hospital , Singapore
[2] Tan Tock Seng Hospital Rehabilitation Centre NHG Health
[3] IREx (Institute of Rehabilitation Excellence)
[4] Lee Kong Chian School of Medicine Nanyang Technological University

BACKGROUND

- Rehabilitation Length of Stay (RLOS) is a **highly tracked indicator.**
- Accurate prediction of RLOS is essential for optimising resource allocation and enhancing patient outcomes.
- Current RLOS is estimated based on clinician's judgement and experience.
- Use machine learning models to categorise patients into **short (≤30 days) or long (>30 days)** based on data available within the first 72 hours of admission.

DATA

- **10,466 records** involving interactions with tertiary rehabilitation from **January 2013 to June 2024**.
- Only data collected within the first **72 hours of admission** were analysed.
- Functional Independence Measure (FIM) scores were extracted from unstructured clinical notes using a combination of **regular expression and large language model**.

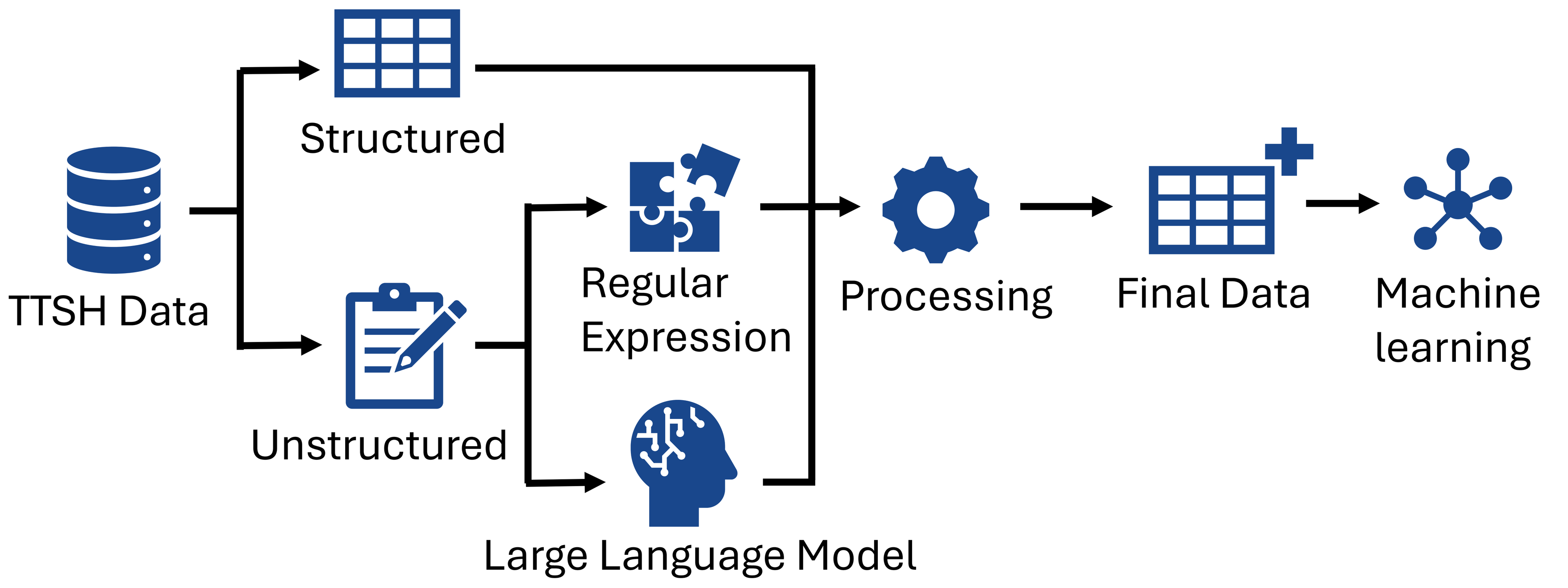
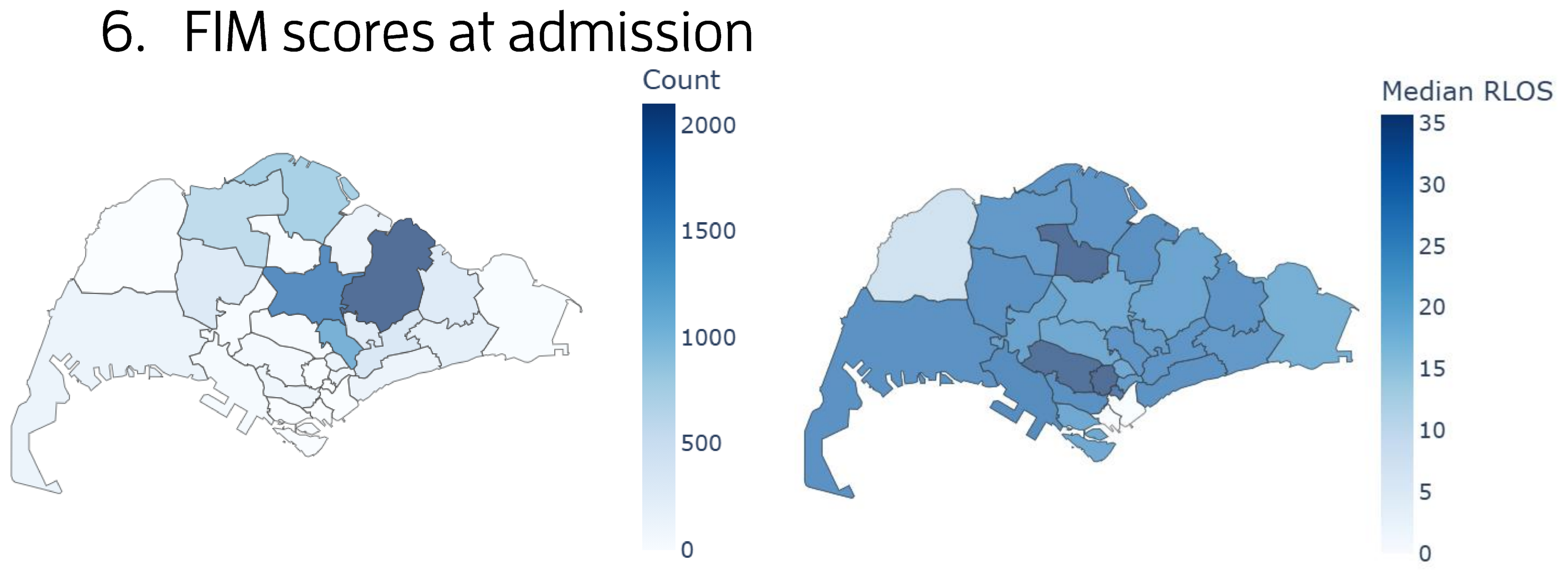


Figure 1: Combining data from structured and unstructured sources.

- Final dataset included **51 data elements** like:
  1. Demographics
  2. Admission details
  3. Clinical information
  4. Types of medications dispensed
  5. Laboratory results
  6. FIM scores at admission



- Approximately half of the patients stayed **near to Tan Tock Seng Hospital**.
- Areas with **higher median RLOS** (~35 days) compared to the median RLOS of 27.0 days include Orchard, Tanglin and Upper Thomson.
- Approximately **43%** of patients with an RLOS of 30 days or less.
- Notable **negative correlation** between admission FIM score and RLOS.

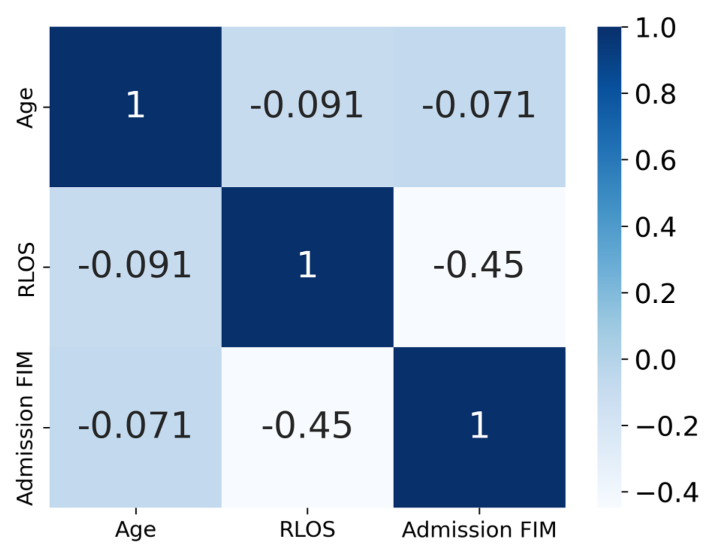


Figure 3: Correlation of numerical features

MODEL TRAINING & RESULTS

- Dataset was split into a train:test ratio of 80:20.
- The models' hyperparameters were optimised using Optuna.
- Comparable mean F1 scores during 10-fold cross-validation across all models tested.

Model	Train	Test			
	F1*	F1	Accuracy	Precision	Recall
LightGBM	0.746	0.716	0.718	0.716	0.718
CatBoost	0.737	0.711	0.711	0.712	0.711
XGBoost	0.747	0.721	0.723	0.721	0.723
Random Forest	0.738	0.707	0.708	0.707	0.708
Decision Tree	0.720	0.695	0.699	0.697	0.699

Table 1: Results from hyperparameter tuning on train set and model evaluation result on test set.
*Mean F1 score for 10-fold-cross validation.

- **XGBoost model** outperformed the others with a test set F1 score of **0.721**.
- It also demonstrated strong performance across other metrics like **accuracy, precision and recall**.

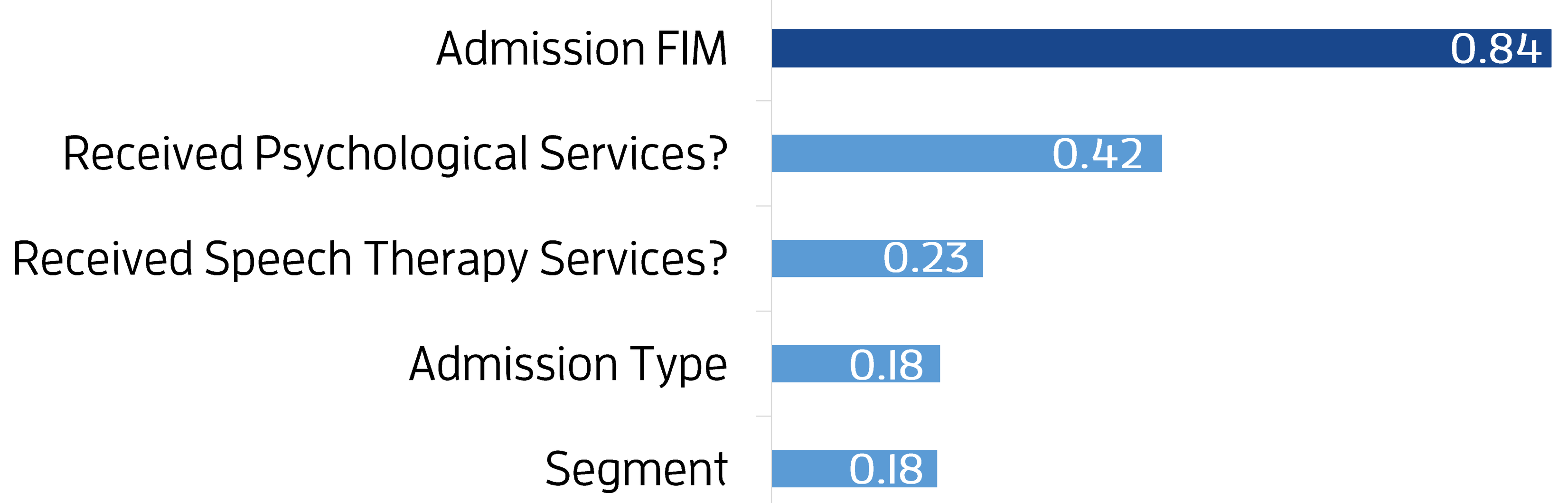


Figure 4: Mean absolute SHAP values of the top 5 features.

- SHapley Additive exPlanations (SHAP) analysis showed that **admission FIM score** had the largest average magnitude of impact on the RLOS categorisation.

DISCUSSION & CONCLUSIONS

- Our machine learning approach for predicting RLOS used data from the first 72 hours of admission shows potential as a **data-driven predictor of RLOS**.
- Clinicians can enter the first 72 hours of admission data into the model to predict which RLOS category it will fall in:

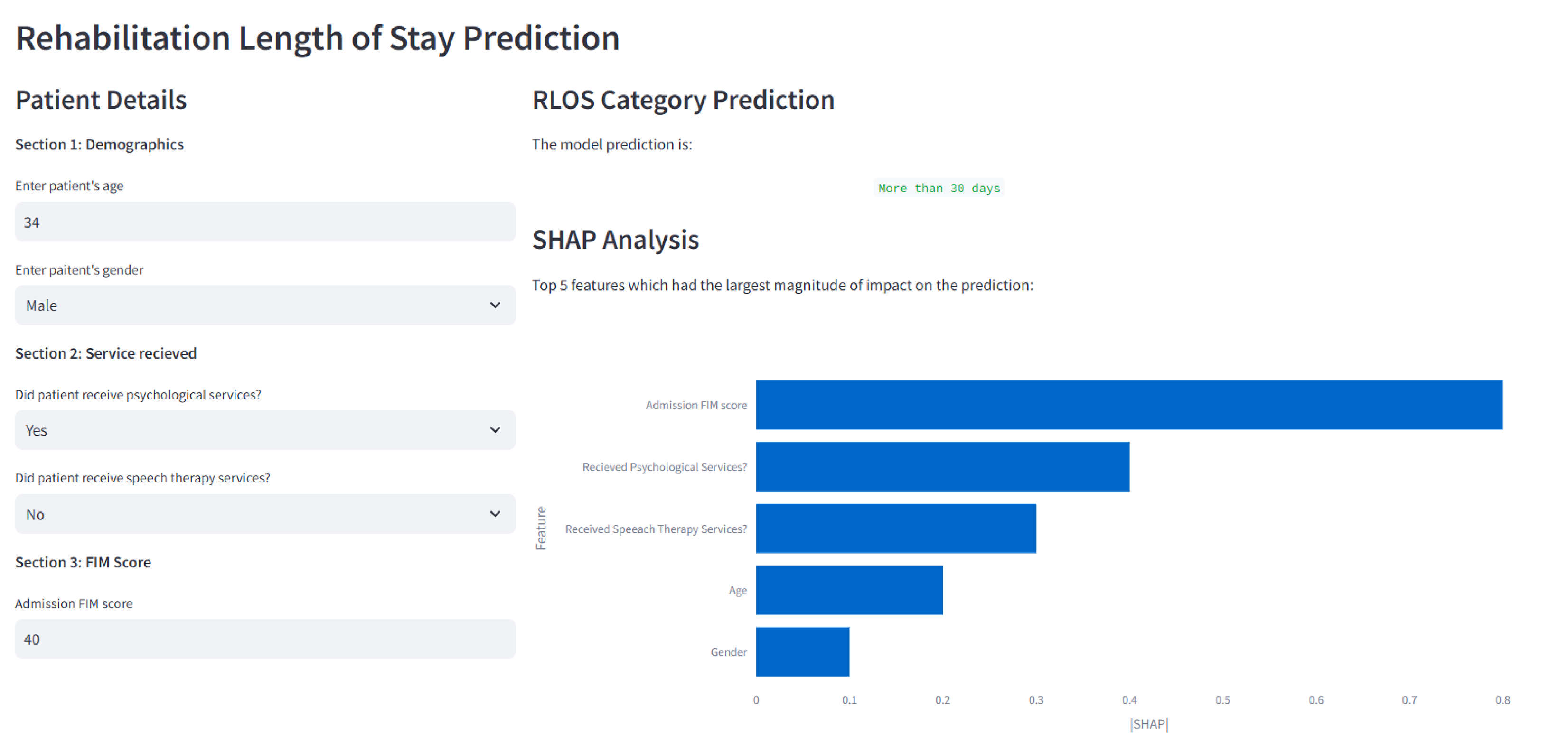


Figure 4: Mock-up application which clinicians could use the model for prediction

FUTURE WORK

- Test the models' predictive capabilities on **newer, unseen data** (after June 2024).
- Explore the **generalisability** of the predictive model by collaborating with other NHG institutions' rehabilitation departments.