## Project Title

A Predictive Risk Index to reduce 30-day Readmissions in NTFGH

## Project Lead and Members

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## Organisation(s) Involved

Ng Teng Fong General Hospital

## Project Period

Start date: 2017

Completed date: 2019

## Aims

Unscheduled readmissions pose additional burden on the healthcare system and are associated with increasing healthcare costs. There are high financial and quality-of-care implications related to frequent unplanned readmissions. Identifying high-risk patients for proactive interventions during hospitalisation and post-discharge may help reduce these readmissions. NTFGH faces one of the highest readmission rates among public hospitals in Singapore, at 14%, which was significantly higher than the national average of 11.3%. There was a significant opportunity for reducing readmissions as one-third of readmissions had been posited to be preventable. This project aims to reduce the readmission rate in NTFGH.

## Background

Ng Teng Fong General Hospital (NTFGH) observed an increasing 30-day readmission rate since its opening in July 2015. A multidisciplinary team was assembled in 2017 consisting of Emergency Department (ED) physicians, Inpatient Clinicians, Nurses and Community Leads. The efforts of the group were coordinated by the Quality, Innovation and Improvement (QII) Department. Scientific literature and best practices pertaining to readmission reduction were reviewed. Many improvement initiatives focused on patients only upon their discharge and readmission. We saw an opportunity to act on patients with high risk for readmission during their index admission before their discharge using data analytics and technology.

Our patient groups included elective and emergency patients admitted to NTFGH. Patients with high risk for readmission were identified using a risk tool developed in-house by analysts from QII with advice from clinical leads. Our Medical Informatics Team deployed the index in our electronic medical record (EMR) system which flagged such patients to frontline clinical teams for action by day two of patients' index admission.

## Methods

See attachment

## Results

Several key process measures that had direct impact to the outcome were tracked weekly. The key processes measured include:

1. Number of patients returning to ED within 30 days of index discharge (and readmitted)
2. Number of post discharge calls made

The outcome measure was the percentage of patients readmitted within 30-days of index admission discharge which was tracked monthly through the Tableau® Dashboard.

We tracked the crude and risk-adjusted readmission rates for NTFGH as the outcome measures. There were significant improvements in the crude rate from 14.1% to 13.0% ($p<0.01$) and the risk-adjusted rate from 11.4% to 10.1% ($p<0.01$) between 2017 to 2019.

## Lessons Learnt

In recent years, the volume of data available in our EMR and administrative systems has grown exponentially. Sophisticated algorithms have been developed to make useful sense of the wealth of data. Data is now a critical corporate asset and analytics will play a key role in further work. Our strategy is to harness machine learning and predictive analytics to extract value from data, such as predictions for high-risk patients for customised interventions.

However, information alone is not useful unless it can be presented meaningfully in a timely manner for decision and action by our care providers. This requires organisation leadership, alignment of priorities and resources, and designing with frontline teams how best to present the information to them. Using a structured improvement approach to test for effectiveness of the interventions was key. We found that pairing improvement methodologies with data analytics and machine learning methods was a powerful way to achieve significant organisation level improvement.

The outcome of this project created unprecedented teamwork towards building a culture of data driven continuous improvement within the organisation

## Conclusion

In developing the model to reduce readmission rate, our process consisted of 3 key steps.

Firstly, in the research and development of the model, it is crucial to include predictors with clinical significance in the modelling for actionable insights. To construct a comprehensive range of possible features, we researched predictors included in literature, obtained inputs from clinicians and conducted feature engineering.

Secondly, deploying machine learning models in EMRs enables the provision of real-time forecasts for patient outcomes. Harnessing EMR for better visualization and high-risk patient flagging allows real-time decision making for frontline staff. This enabled us to better plan the use of our limited healthcare resources to drive improvements.

Thirdly, it demonstrated that significant reduction in 30-day readmission rates could be achieved with the Predictive Risk Index deployment and bundled interventions. Building on our learning experience, our readmission risk index had been adopted by the New Generation EMR (NGEMR) project for implementation across the National University Health Systems (NUHS) and National Healthcare Group (NHG) clusters.

The model can be generalised to other cohorts as all predictors can be obtained upon admission at any acute hospital, but it needs to be validated for use on different groups of patients for generalisability purpose

## Project Category

Automation, IT & Robotics, Innovation, Care Redesign

## Keywords

Automation, IT & Robotics, Quality Improvement Tools, Ng Teng Fong General Hospital, Electronic Medical Record, Dashboards, Data Visualisation, Machine

Learning, Predictive Analytics, Model for Improvement Framework, Improvement Tool, Plan-Do-Study-Act, Readmission, Heatmap

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# A PREDICTIVE RISK INDEX TO REDUCE 30-DAY READMISSIONS IN NTFGH

☑ CARE REDESIGN
❑ WORKFORCE TRANSFORMATION
☑ AUTOMATION, IT, ROBOTICS INNOVATION

MEMBERS: CHRISTINE WU XIA, FRANCIS PHNG WEI LOONG, TAI KAI PIK, KELVIN LEW SIN MIN, DR HWANG CHI HONG, KUTTIAMMAL SUNDARASAN, A/PROF GAMALIEL TAN YU-HENG, A/PROF GERALD CHUA SENG WEE

## 1. Define Problem, Set Aim

**Background**

- Ng Teng Fong General Hospital (NTFGH) faces one of the highest readmission rates among public hospitals in Singapore, at 14%.
- Unscheduled readmissions pose additional burden on the healthcare system and are associated with financial and quality-of-care implications. Complex underlying medical conditions and complex social issues were 2 key reasons for these readmissions.

**Problem/Opportunity for Improvement**

- Identifying high-risk patients for proactive interventions during hospitalisation and post-discharge may help reduce these readmissions. We saw an opportunity to act on patients with high risk for readmission during their index admission before their discharge using data analytics and technology.
- To steer and guide improvement efforts, a multidisciplinary team was assembled in 2017 consisting of Emergency Department (ED) physicians, Inpatient Clinicians, Nurses and Community Leads. The efforts of the group were coordinated by the Quality, Innovation and Improvement (QII) Department.

**Aim**

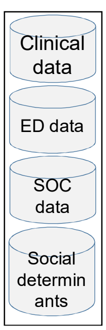
- To reduce readmission rate from 14% to 12% in NTFGH by 2020.

## 2. Strategy for Change

**Real-time Patient Stratification in EMR**

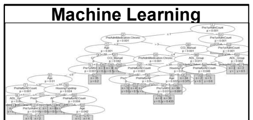
- In-house machine learning models were built to determine which patients are at higher risk of readmission during day 2 admission. The optimal model was deployed in the EMR system for real-time operational interventions. High risk patients are flagged in EMR to frontline staff.

**1. EMR**




**2. Model Development & Selection**

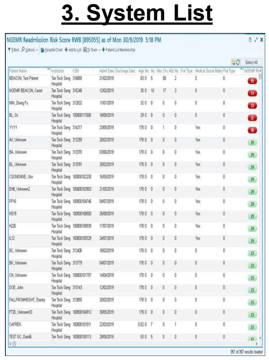
Machine Learning



Optimal Predictive Risk Index

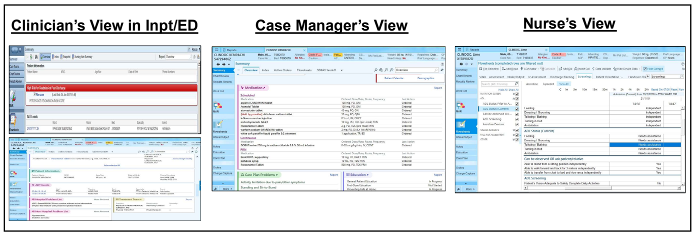
| Variables | Beta Coeff |
|---|---|
| Intercept | -3.36 |
| 1. Patient's age (year) | 0.01 |
| 2. Patient staying at 1-room flat, institution or homeless, yes/no | 0.24 |
| 3. No. of pre 1yr hospital admissions, n | 0.24 |
| 4. No. of pre half yr emergency attendances, n | 0.08 |
| 5. Pre 1yr Medical Social Referral, yes/no | 0.28 |
| 6. Functional Components: | |
| - Dependent | 0.39 |
| - Needs Assistance | 0.19 |
| - Independent | 0.00 |
| 7. Charlson Comorbidity Index | 0.07 |
| 8. No. of Preadm Chronic Medication | 0.05 |

**3. System List**



**4. Frontline View**

Clinician's View in Inpt/ED — Case Manager's View — Nurse's View



## 3. Interventions and Results

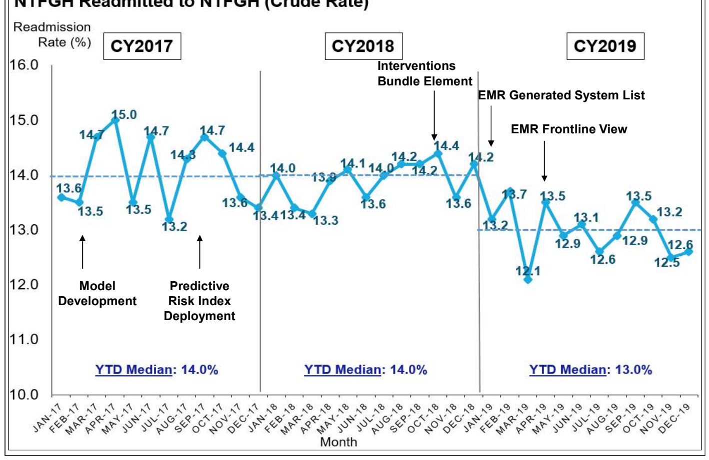
**30-day Readmission Intervention Bundle Elements**

- We used the Quality Improvement framework to identify the problem and formulate bundled interventions for reducing readmissions at several fronts. Risk stratification enabled the teams to better align resources to the higher risk patients and enable sustainability in the long term.

| S/N | Intervention Bundle elements | Risk Score | |
|---|---|---|---|
| | | Low | High |
| 1 | Risk stratification | X | X |
| 2 | Comprehensive & collaborative discharge summary | X | X |
| 3 | Post discharge phone call | | X |
| 4 | Post hospital Home Visit | | X |
| 5 | Active case assessment of Readmitted cases weekly | | X |
| 6 | Weekly monitoring of patients returning to ED within 30 days of discharge | | X |

**Improvement in 30-day Readmission Outcomes**

- We tracked the crude and risk-adjusted readmission rates for NTFGH as the outcome measures. There were improvements in the crude rate from 14.1% to 13.0% (p<0.01) and the risk-adjusted rate from 11.4% to 10.1% (p<0.01) between 2017 to 2019.




## 4. Learning Points

- Organisation leadership, alignment of priorities and resources, and designing with the frontline teams how best to present the information to them were crucial in enabling this project.
- Harnessing machine learning and predictive analytics with clinical significance, real-time stratification and identification for targeted/Bundled interventions and providing insights to frontline staff for real-time decision making.
- Quality Improvement Frameworks created the structure for problem solving and intervention formulation.
- Building on our success, we shared our model with other institutions, and it has been adopted by NGEMR team for implementation across National University Health System (NUHS) and National Healthcare Group (NHG) clusters.

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