Predictive Risk Score for Reducing 30 Day Readmissions

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Executive Summary

In 2016, the 30-day readmission rate of Ng Teng Fong General Hospital (NTFGH) was 13.2%, which was significantly higher than the national average of 10.5% among the public hospitals in Singapore [1]. A multidisciplinary team of clinicians and other care providers who supported case management and community operations were assembled to tackle the problem of high readmissions. A risk score for real-time prediction of readmissions for hospitalized patients was developed using machine-learning models and deployed in Electronic Medical Records (EMR) in 2017. Systematic prompts of high-risk patients in the EMR enabled healthcare workers a greater degree of prioritization to intervene on patients in need. With the implementation of this risk score and targeted interventions on high-risk patients, the overall 30-day readmission rate of NTFGH significantly improved from 15.0% in April 2017 to 12.0% in February 2020 ($p < 0.01$).

Define the Clinical Problem and Pre-Implementation Performance

Unplanned readmissions to a hospital places a significant strain on the healthcare system and aggravates the bed crunch faced by public hospitals in Singapore. High readmissions impose significant financial and quality-of-care implications. In 2016, NTFGH's 30-day readmission rate was 13.2%, which was higher than the national average and was one of the highest amongst other public hospitals in Singapore.

The Ministry of Health (MOH), Singapore defines 30-day readmissions as the percentage of inpatient discharges with emergency readmissions within 30 days of initial discharge due to all causes. The denominator of the 30-day readmission rate calculation is formed by all discharges after excluding in-hospital deaths, transfers-out to other hospitals, and cases of cancer, HIV, and certain types of trauma [2].

The 30-day readmission rate is also one of the MOH pay-for-performance (P4P) indicators which are the priorities identified by MOH that strive towards building a more sustainable healthcare system. Hospitals that are performing well on the P4P indicators will be rewarded. In other words, the level of reimbursement that the hospitals receive will increase for those who have met the target for the P4P indicator.

Patients who were readmitted to a hospital within 30 days tended to have multiple admissions over a one-year period due to complex underlying medical conditions and complex social issues [8]. These were similar reasons seen in the patients admitted to NTFGH and one-third of readmissions had been posited to be preventable [13].

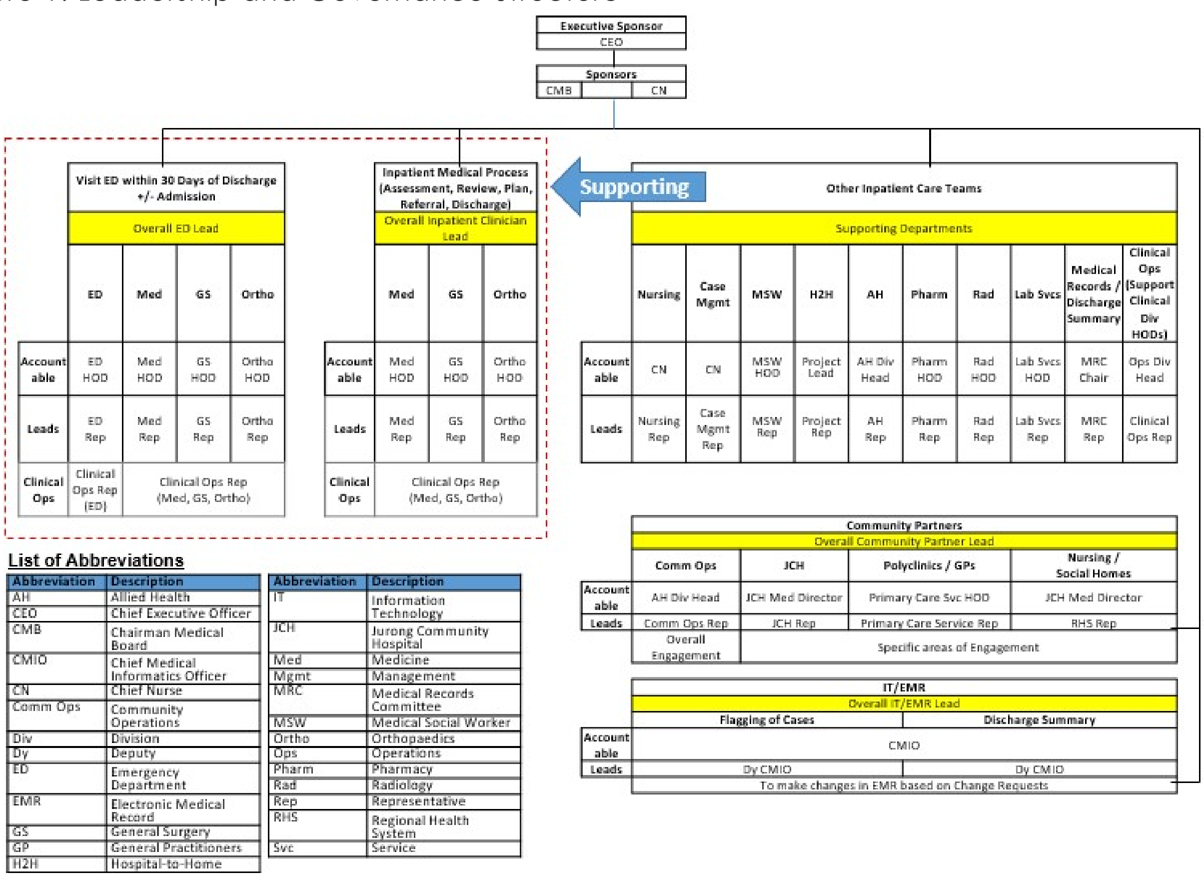
This highlighted an opportunity to act on patients with high risk for readmission during their index admission before their discharge - to proactively identify and attend to patients who are at risk for readmission before an actual readmission occurred by leveraging on the strength of data analytics and technology.

Design and Implementation Model Practices and Governance

Attempts at reducing readmission takes a holistic approach covering multiple streams; ranging from the Emergency Department (ED) to inpatient care delivery and post discharge care and coordination. The execution could only unfold smoothly after a series of careful planning that was spearheaded by senior executive leadership to establish the organisation structures and resources required (Figure 1), and also the management framework for the routine tracking of progress and performance.

These multi-disciplinary efforts were coordinated across the ED, various inpatient teams, community partners, and the IT and EMR teams (for system-related support). Clinical inputs were sought from the clinical champions that included physicians, nursing case managers, and Allied Health Professionals such as pharmacists, therapists, dietitians, and medical social workers, to identify opportunities for intervention throughout the patient's journey in order to firm up the care template. To smoothen out the operational processes, respective leads from each of these practices met up on a weekly basis for the Multi-Disciplinary Meeting (MDM) to facilitate discussions and coordination.

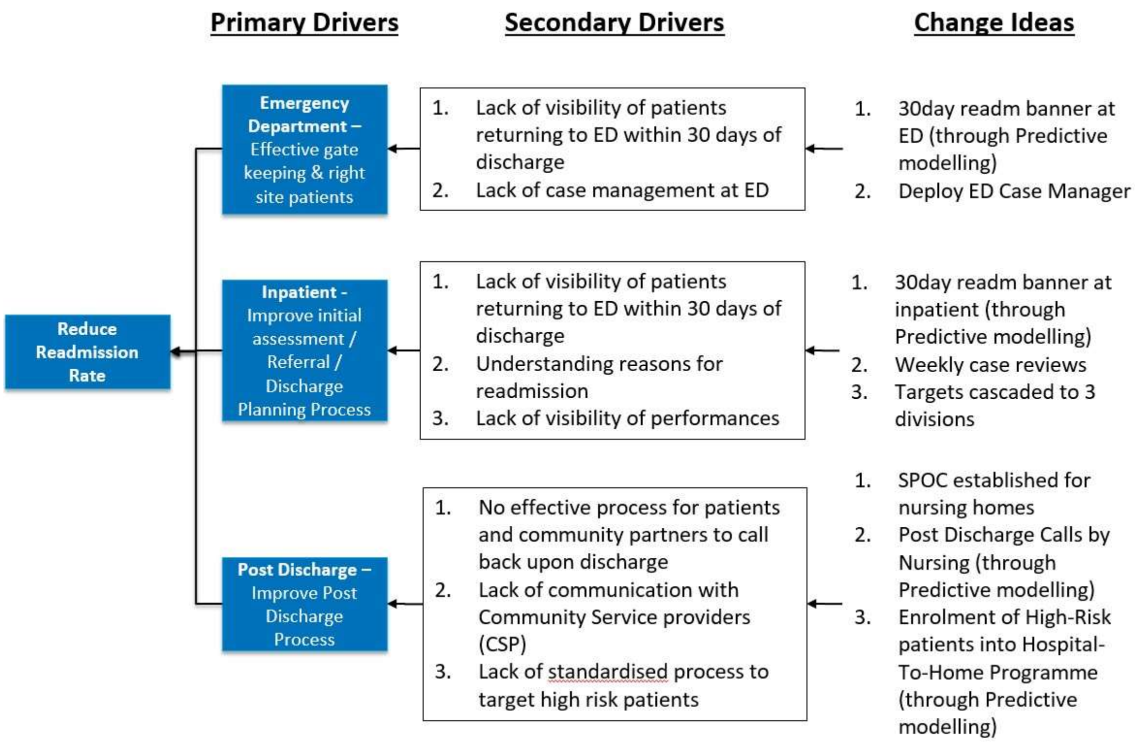
Figure 1: Leadership and Governance Structure



Improvement science methodologies such as Model for Improvement also provided a structured approach for project teams to align their aims, select measurements and test interventions. A Rapid Improvement Event, facilitated by the Quality, Innovation and Improvement (QII) team, was conducted to walk through the end-to-end process of a patient's care journey using process maps (Figure 2). Potential root causes of readmissions were identified so that the process owners could take up the issues and brainstorm for ideas to resolve them.

Implementing any new workflow requires a deliberate approach to "unlearn to re-learn" and a set of Standard Work was implemented as part of the strategy to sustain the improvement efforts. QII staff undertook regular audits in the initial phase to ensure that all parties adhered to the process.

Figure 2: 30-day Readmissions Driver Diagram



In terms of model development, a variety of tools for predictive modelling and intervention programs were available in the United States and other countries to identify patients with high risk of readmission [3-7], but the majority of these efforts were largely clinical-based and aimed at addressing readmissions from a medical perspective. Kaiser Permanente Southern California adopted the widely recognised Canadian LACE index and demonstrated significant reduction of readmission rates with a set of targeted care bundles that focused on social aspects of care [8]. This strategy was aligned with the operational needs of our hospital in view of the common sightings of patients who were readmitted due to unmet social needs, and the need to better apportion our limited medical resources to patients who require it the most.

A customised risk score was further developed by NTFGH QII analysts by taking reference from the Canadian LACE index and other significant parameters in the local setting such as socio-economic and functional status. This enhanced risk score was then deployed in the EMR system by the Medical Informatics team to flag out high-risk patients to frontline clinical teams. The improved visibility of high risk patients in EMR also opened windows of opportunities for intervention by different care providers involved throughout the patient's care journey. This formed the basis of our multi-pronged intervention care bundle system (Figure 6) that involves the contributions from a multi-disciplinary care team to effectively address different domains of care and other potential risks of readmissions.

In addition, there is a need for the front end view to be customised to cater to the operational needs of the care providers. In the case of the case managers, instead of merely being a black box algorithm, the system not only flags out the risk score of patients, but also displays the factors contributing to the readmissions risk (Figure 3). This integrates with and supports existing clinical workflows and assessments to deliver personalised patient care, especially when a patient receives a higher than expected risk score. It also translates into an intuitive and seamless adoption of the risk score by the care providers, which is reinforced with on-the-job training.

Figure 3: Customised Front End View of the Risk Score for Different Healthcare Provider (Example for Case Managers)

Clinical Transformation enabled through Information and Technology

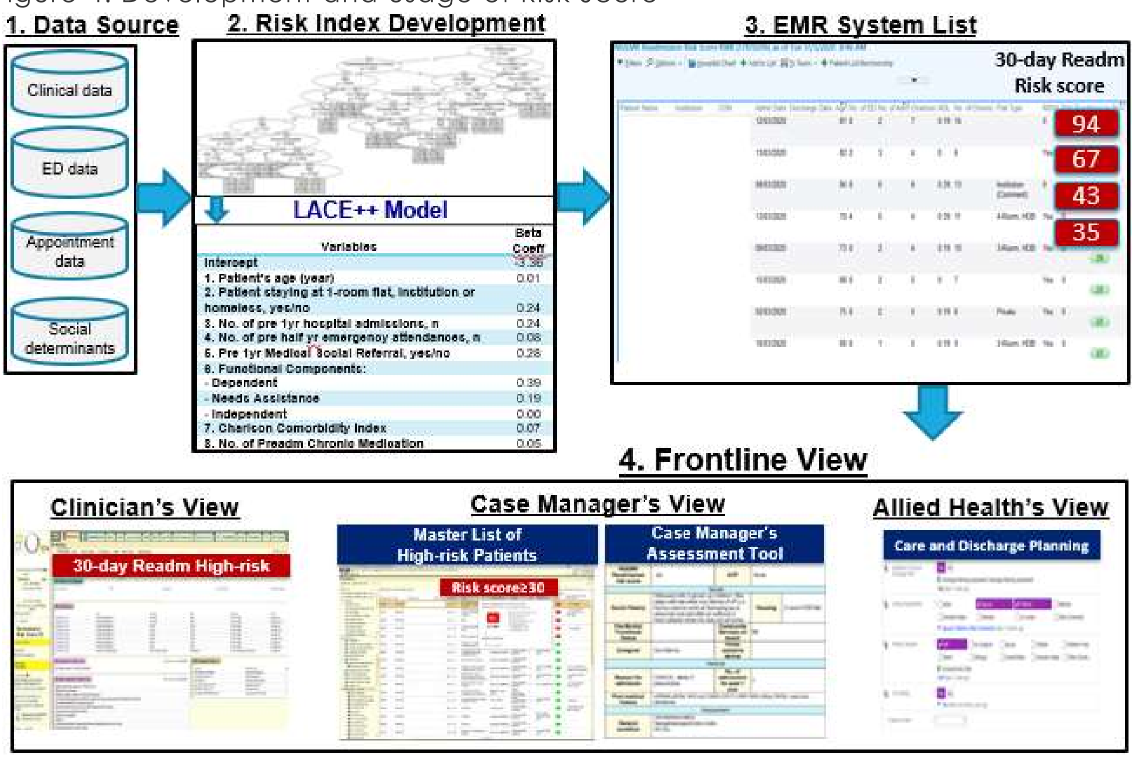
Model Development - Data

Electronic health records of 25,472 patients discharged from NTFGH's Medicine Department between January 2016 and December 2016 were retrospectively extracted from different clinical settings – inpatient, outpatient and ED in our hospital's Epic EMR. This included the patient demographic profile, medical diagnosis, previous emergency attendances and hospitalisations, and proxy measures of socio-economic status such as place of residence (e.g. in a government-owned rental flat) and records of medical social referral.

Model Development – Methods

Machine-learning models were built to estimate the probability of readmission within 30 days (Figure 4). A split-sample design was applied on our data to derive and internally validate the predictive model. The dataset was randomly split into two: 70% for model derivation and 30% for model validation.

Figure 4: Development and usage of Risk Score



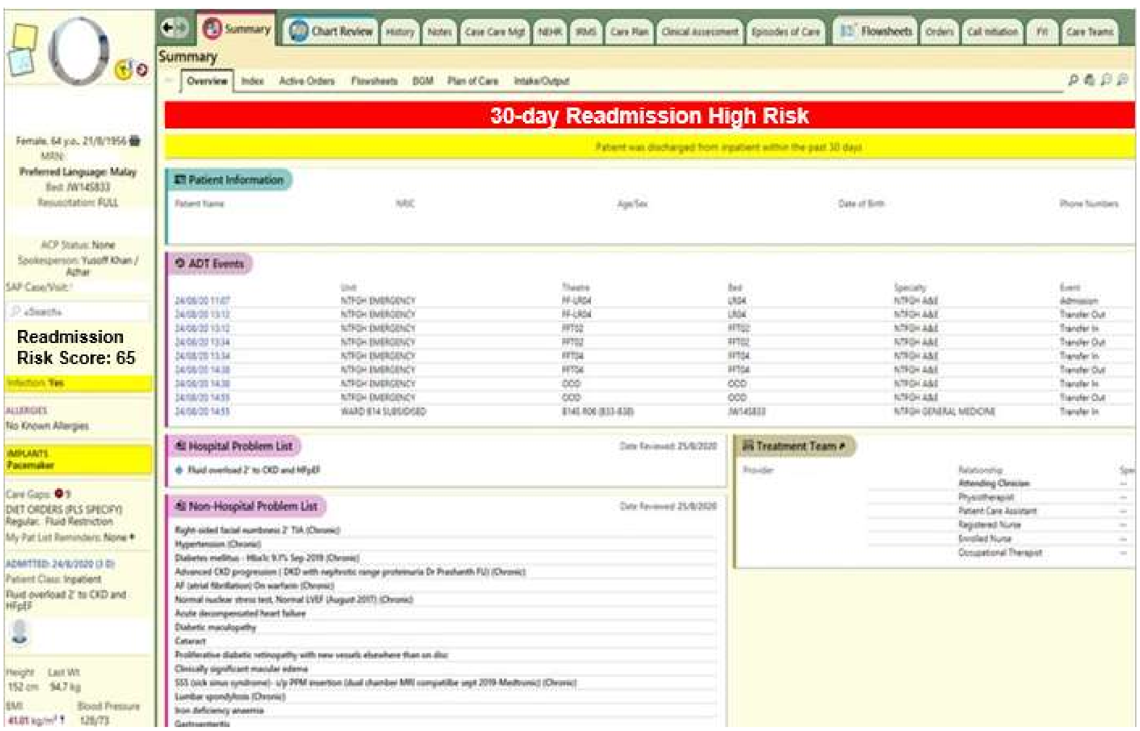
Logistic regression was used to measure the effect of predictors associated with 30-day readmissions. Gradient boosted machine method builds the model in a stage-wise boosting method and generalizes them by allowing optimization of an arbitrary differentiable loss function. Random Forest is an ensemble learner that generates many decision trees and uses majority 'voting' of all the trees' outcomes to decide on the binary classification [14]. Goodness of fit tests such as Hosmer–Lemeshow test and Out-of-bag cross-validation were conducted to examine the model calibration of the corresponding machine learning models.

Deployment of Real-time Risk Flagging

The optimal risk score from the machine-learning models was deployed in EMR using Predictive Model Markup Language and displayed at the patient's storyboard and system list with real-time patient's information. The contributing factors of the risk of readmissions were also displayed in the list to provide clinical decision support for the inpatient medical, nursing, case management, ED and post-discharge care teams in addressing the needs of high-risk patients before readmissions arise [8,11].

The building of the readmission risk score into the EMR, along with the customized front end view, generated a significant improvement in the visibility of high risk patients. For the ED setting, case managers would be activated to interact with these high-risk patients and right siting them appropriately. In the inpatient setting, high-risk patients would be easily sieved out for proactive interventions through the banner alert in the admission encounter of the EMR (Figure 5). The horizontal bars on the top highlights different patient characteristics which may affect the patient's care. The red horizontal bar indicates a high 30-day readmissions risk, with the corresponding risk score seen on the left column. This allows clinicians to update the patient care during their daily ward rounds, look at the patient's clinical data in greater detail, identify medical conditions, and the need for early referral for social issues such as to the case managers and the medical social workers.

Figure 5: Alert for 30-day Readmission High-risk Patients through the Banner in EMR



For case managers, their overall focus lies with their accountability towards each patient as defined by the individual patient's needs. Fundamentally, their role in the management of readmissions involves establishing effective communication among patients, their families and the different care providers in order to work out the arrangements to address the patient's needs. They also follow up closely for the identified patients to ensure that the needful is done. As an example, for high-risk patients who may be dependent for the activities of daily living and require higher care needs, case managers will refer them to the appropriate community care providers on top of the standard care provided. They will subsequently follow up with post discharge calls to ensure that the patient's needs are tended to sufficiently. All these activities are facilitated by the case management module in the EMR that allows for easy identification of high risk patients and tracking of interventions as well as post discharge follow-ups. The documentation of post discharge call was subsequently tracked in the EMR to minimize any deviation in the process, and it took approximately 3 months before the practice became a "new norm".

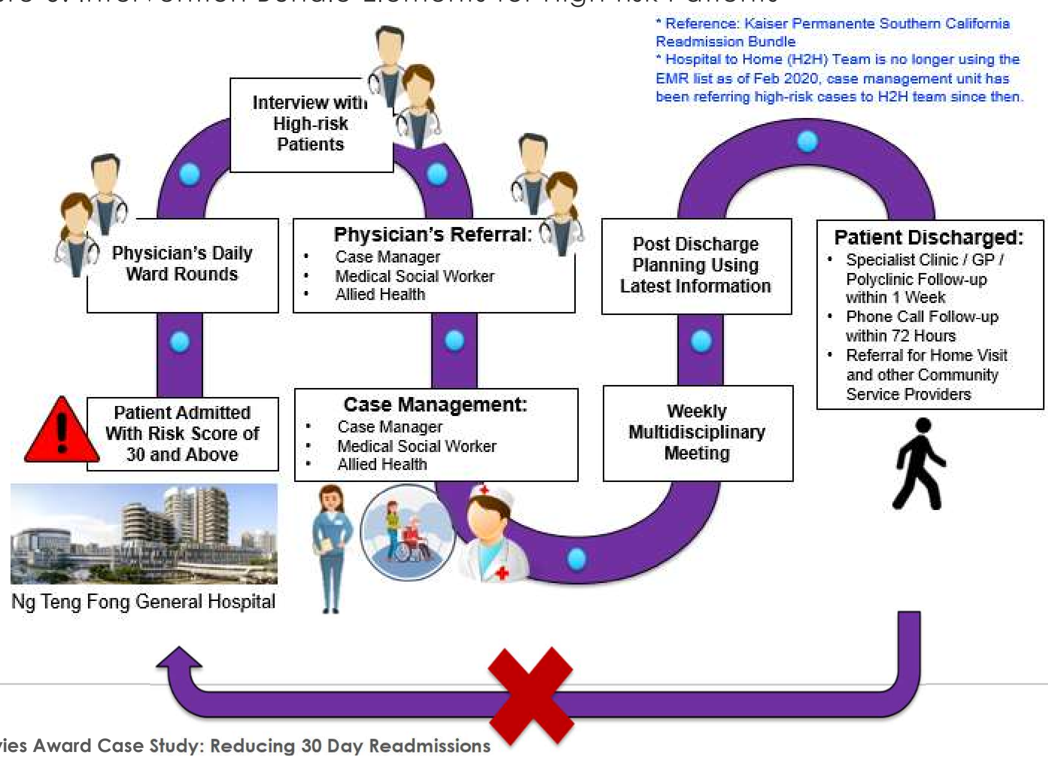
Additionally, backend processes will be triggered in the EMR to constantly reflect the latest information of for patient once it becomes available, and this allows for real-time decision making and planning for frontline staff. Some examples are:

- Three hot clinics were created every week for the general medicine teams to refer patients with higher risk score. These patients were promptly followed up with and seen within a week.
- The "discharge memo" is populated with more details on the treatment plans. These plans are conveyed to the general practitioners, especially for patients with a higher risk of readmissions.
- A dedicated team, including one consultant and junior doctors, goes to the ED when a patient re-presents within 30 days. The predictive risk score has enabled the ED doctors to focus on these patients with a higher risk of readmissions.

Implementation of Interventions

Intervention care bundle elements were developed and implemented based on identified gaps and evidence pertaining to readmission reduction [12], as illustrated in Figure 6.

Figure 6: Intervention Bundle Elements for High-risk Patients



During the daily ward rounds, Physicians attend to patients and are able to access the patient's salient information through the EMR view which highlights different factors that may affect patient care. This allows the clinician to update the patient care, and as a result, look at the patient clinical data in greater detail and identify medical conditions or the need for early referral for social issues such as to the case managers, medical social workers or allied health professionals.

For case managers, as they have a greater clinical view over the existing care service providers, they are better able to refer patients to the appropriate care programs. They will also liaise with the medical social worker to run through the progress of the patients and coordinate better care plans for them to prevent prolonged inpatient stay and lower risk of readmissions. Case managers are also assisted by the use of the assessment screening tool which helps to improve patient assessment and highlight issues such as unmet social needs.

For high-risk patients who did not comply with assigned follow-up care and medication compliance, case managers would also initiate home visit to assess how these patients are coping at home and if there are any other challenges faced by the patients. Complex cases would also be flagged out for further discussions at the weekly MDMs to determine the appropriate response.

With the documentation of the post discharge calls being established as part of the standard workflow in the EMR, there is now a structured approach for case managers to follow up with patients. This serves to ensure greater consistency in the standard of care delivered by verifying the adequacy of the current care plans. The information can also be extracted from the EMR to facilitate performance management efforts, which drives accountability at the individual level and reinforces efforts for following up and closing the feedback loop with our patients. This would also be taken into consideration in the evaluation of the case manager's performance aside to the actual readmission outcomes.

Post-discharge Phone Call

Follow-up phone calls after hospital discharge have shown to reduce readmission rates [14]. Thus, we developed a program for post discharge nurses to call all high-risk patients within 72 hours after hospital discharge. These calls are designed to identify risk factors for readmission by focusing on education and review of the recent hospitalization such as identifying early treatment failures, medication adverse reactions, social issues, treatment plan compliance, and reconciling all medications.

Post-hospital Home Visit

Case managers would conduct home visits to the high-risk patients who are assessed to be not complying with assigned follow-up care to ensure smooth post-discharge transition and holistic coordinated care in the community, and to prevent medical complications and readmission.

Post-hospital Visits at Specialist Clinic or Polyclinic within 1 Week

Hernandez et al [15] reported a correlation between time of post-hospital visit and risk of 30-day readmissions. A centralized contact center for National University Polyclinics provides a follow-up appointment date within three days of request. Should the patient not be given the appointment date upon discharge, a hospital clerk will inform the patient via telephone calls. This ensures timely review in outpatient clinics, which is typically scheduled within a week post discharge.

Weekly Multidisciplinary Meetings

Many of the patients who are readmitted to the hospital have multiple hospital admissions over a one-year period. Patients who stay more than 14 days in hospital are brought up for discussion at a weekly multidisciplinary meeting made of up physicians, therapists and a medical social worker. At the meeting, team members share and identify gaps in patient care, access to resources, barriers to discharge and create an individualized care plan.

Early Intervention at ED

At the ED, patients with high-risk of readmissions could be quickly identified upon registration, which serves as a reference guide for corroborating with the reasons for the re-attendance. As a result, case managers are able to initiate early discussions with physicians and perform early interventions as appropriate. In some cases, this may even break the cycle of readmission by addressing the actual needs of the patient prior to the admission.

Improving Adherence to the Standard of Care

Post discharge calls were measured in order to facilitate the compliance of targeted interventions, and consequently, consistency in the standard of care delivered.

Post discharge call is a crucial element especially for high-risk patients as this allows the post discharge nurse to have a preliminary assessment on adequacy of the current care plans, the patients' medical needs and identify any opportunities for intervention prior to the occurrence of an avoidable hospital visit. The information for post discharge calls conducted is captured in the EMR and is recommended to be completed for a patient within 72 hours post discharge (Figure 7).

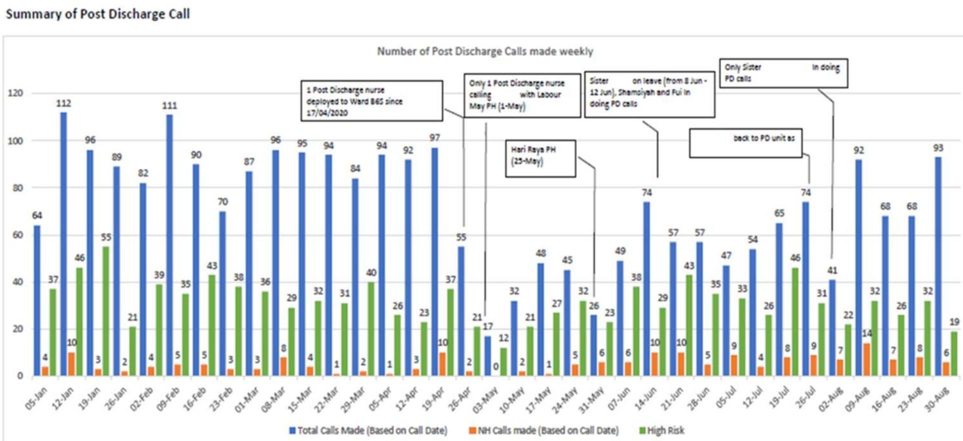


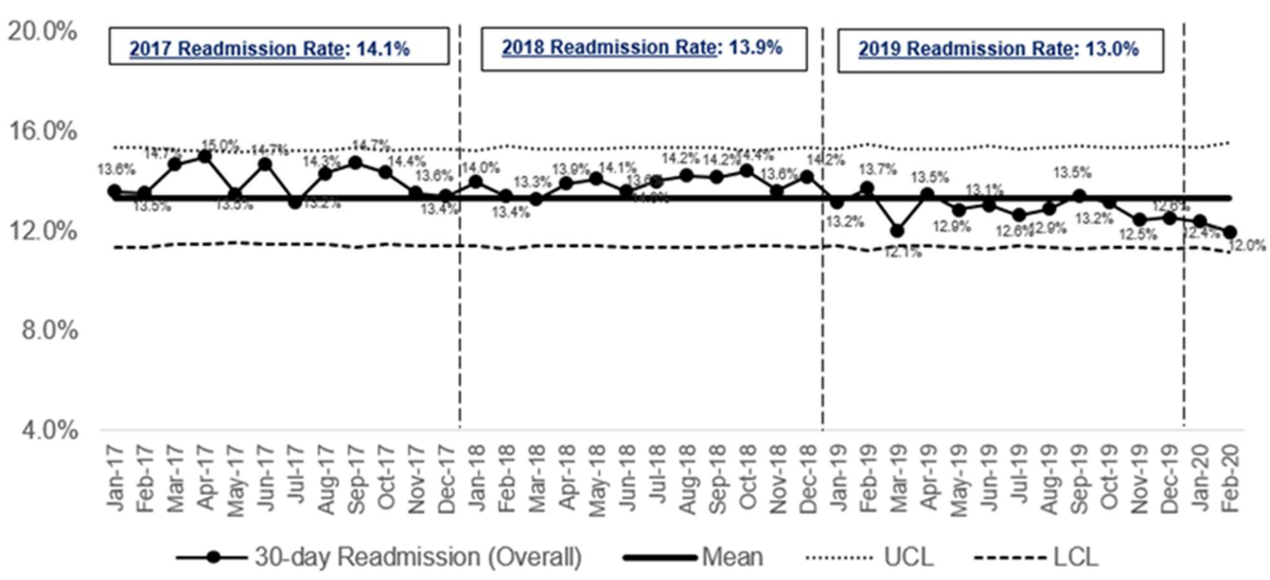
Figure 7: Summary of Post Discharge Calls

Improving Patient Outcomes

With the improving adherence to the clinical practice and the implementation of targeted interventions, there were improvements in 30-day readmission rates for our institution.

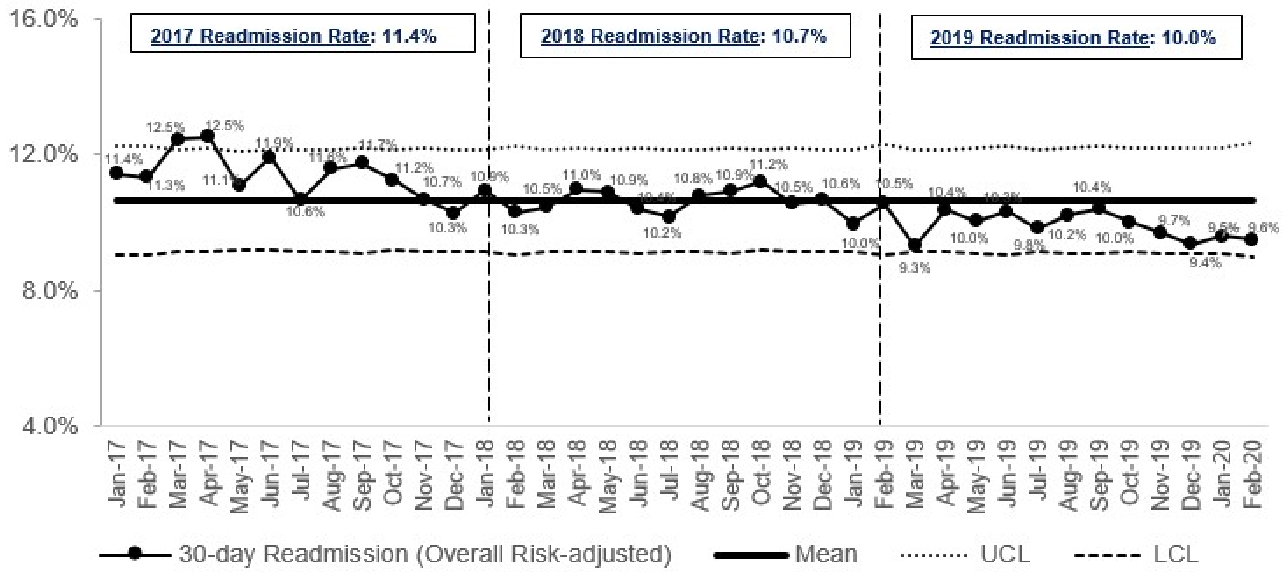
The overall 30-day readmission rate of NTFGH improved from 14.1% to 13.0% ($p < 0.01$) between CY2017 to CY2019 (Figure 8). If we had considered our journey since the start of FY17 instead, we would have achieved a notable numerical reduction in readmission rate from 15.0% to 12.0% ($p < 0.01$).

Figure 8: NTFGH Overall 30-day Readmission Rate Trend Line



To account for possible differences in the baseline patient profile, we also compared the overall risk adjusted 30-day readmission rate and the conclusions corroborated with the above. Similarly, there was also an improvement from 11.4% to 10.0% ($p < 0.01$) between CY2017 to CY2019 (Figure 9).

Figure 9: NTFGH Overall Risk-Adjusted 30-day Readmission Rate Trend Line



Accountability and Driving Resilient Care Redesign

The implementation of the risk score brings about real-time clinical decision support and improved visibility of the high risk patients throughout the patients' journey – from the ED visit to inpatient admission encounter as well as post discharge. Every patient presents their own set of medical and non-medical issues to be addressed. Similarly, our care plans ought to be tailored accordingly to resolve these issues. Based on the patients' journey, a multi-pronged care bundle system involving the collaborative efforts of a multidisciplinary care team across different checkpoints is actualized to specifically identify our patients' needs that would potentially result in an avoidable readmission. This allows the care teams to proactively design or even personalize care plans.

Additionally, it also enables early detection of any gaps or need for additional attention or assistance through a structured approach for following up with high risk patients so as to prevent the occurrence of any avoidable readmissions, thereby providing opportunities to improve care delivery. As the information can also be extracted from the EMR to facilitate performance management efforts, this indirectly drives accountability and adherence to the standard of care delivered for our patients.

With the availability of system level information for performance review as well as observations drawn from day to day execution, any areas for improvements in performance would also be flagged out for discussion and action at the weekly MDMs. Constructive feedback is routinely provided by senior members of the case management team to ensure that the care delivered is up to mark. Should there be any gaps in care standards delivered by the case manager, they would then be placed under close supervision from the seniors and be closely guided so as to build up their proficiencies at the individual level. The intended goal is for these case managers to be able to discharge their daily duties independently.

Conclusion

A risk score using NTFGH data was derived and validated, with good discriminative power and acceptable calibration for predicting the risk of 30-day readmissions [3]. Using eight predictors, the risk score flagged the top 10% of patients as high risk, with an approximate 40% risk of readmission within 30 days of discharge.

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 enables a better planning of healthcare resources to drive improvements.

Essentially, the reduction of readmissions would require a better control of not only the underlying medical conditions, but also other complex social issues. This involves a continuous effort that encompasses both systematic and multidisciplinary approaches that is steered by an established governance structure in order to address the multi-dimensional contributors of readmissions.

Besides, it is critical to determine the main reasons resulting in the patient's readmission so that these issues can be adequately addressed, particularly so for recurring cases. Particularly in the case of patient outliers, the case management team will provide further assessment after the patients are flagged out and effective communication has to be established with the patients, their families as well as the different care providers in order to identify and address the root cause of the readmission.

On top of the interactions with patients and their families, another critical communication platform would be the weekly MDMs to facilitate exchange of information and ideas between care provider that may possibly trigger other useful interventions with a greater degree of personalized care for our patients. All of these would culminate in ensuring the continuity and operational success of our readmission reduction efforts.

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HIMSS Global Conference Audience Guidance (This will not be published)

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