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CONFERENCE ABSTRACT

Identifying prospective frequent readmitters for hospital to home intervention using machine learning

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Introduction: Singapore is a developed country with a population of 5.6 million and an acute-centric healthcare system. While the acute hospitals deliver extensive care, patients with multiple care needs face challenges in managing their conditions post-discharge, due to various reasons, such as weak caregiver support. This phenomenon is especially evident in older and frail patients who are frequently readmitted as their condition(s) deteriorate post-discharge.

Methods: In April 2017, Singapore's Ministry of Health (MOH) launched a nationwide Hospital to Home (H2H) care model to provide holistic patient-centric care to support patients discharging from public hospitals, so that they can transit back home, and stay well in the community. H2H targets high healthcare utilizers who are frail with complex care needs. The service includes medication reconciliation, case management, care coordination, telephonic support and caregiver training. To facilitate the development and deployment of the predictive model to risk stratify and segment the patients for enrolment assessment into H2H, a workgroup consisting of clinicians and data scientists across the various public hospitals was formed. The dependent variable for the model was three or more non-elective inpatient admissions within a 1-year period. Independent variables, generated based on literature review and input from clinicians and care managers, were segmented into 3 primary categories: sociodemographic, past hospital utilization and past medical conditions.

Results: The top important variable was "total LOS in the past 12 months" followed by "number of days from previous non-elective admission" which lifted the model performance significantly.

The best performing machine learning algorithm has an AUC of 0.79, recall of 39%, with precision set at 70% after consultation with the H2H clinical committee to capture very high risk patients.

The prediction list, generated on daily basis, is now an integrated part of patient assessment workflow. The list helps the care team to support and follow up with the high healthcare utilizers and their caregivers after discharge. As of Oct 2018, more than 23,000 patients had benefited.

Conclusions: The predictive model exemplifies the benefit of augmenting prediction model with clinical assessment. By having the prediction tool act as a bigger "sieve" to do the first level of filtering and the subsequent removal of potential false positives by clinicians when they assessed the patient in-ward provides a targeted intervention with minimal clinical resources.

Lessons learnt: To manage the multidisciplinary development team in this endeavour efficiently, we adopted an iterative development process that allow us to fail fast and often.

To convince clinicians to shift their decision making process to be augmented with a predictive model, we engaged reputable clinicians in the H2H clinical committee and analytics teams from different public hospitals to co-develop the model.

Limitations: In this discussion, we had not been able to cover in depth on areas such as comparing the predictive model performance with different set of features.

Future research: Future enhancements include the use of Natural Language Processing on unstructured clinical notes to extract care-giver and non-clinical information as additional features for the prediction model.

Keywords: multiple readmission; electronic health record; machine learning; community-centric intervention; digital health; risk prediction; risk stratification