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Calibrating Readmission Risk Prediction Models for Determining Post-discharge Follow-up Timing

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Abstract

The soaring hospital readmission rates are straining the already limited financial resources in the US health system. Meanwhile, timely outpatient follow-up, an efficient and cost-effective intervention following hospital discharge, has been shown to reduce the readmission risk. However, the current and projected shortage of physicians in primary and specialty care poses a unique dilemma in transitional care planning: optimizing the utilization of post-discharge follow-up to reduce readmission rate while limiting the strain on the limited pool of outpatient physicians. The ideal solution would entail a strategy whereby patients at higher risk for readmission are stratified towards earlier outpatient follow-up and vice versa. This article explores the utility of Institution-specific readmission risk prediction algorithms for assessing patient population for diverse administrative, clinical and socioeconomic risk factors and further classifying the hospital's patient population into high- and low-risk strata, so that appropriate risk-concordant timing of follow-up can be assigned at the time of hospital discharge, with earlier follow-up assigned to high readmission risk strata. This stratification shall help ensure judicious and equitable human resource allocation while simultaneously reducing hospital readmission rates.

Keywords: Post-discharge follow-up, Readmission risk, Institution-specific, Risk prediction models

W hile caring for a diverse patient population, determining the appropriate timing for post-hospitalization follow-up of patients with their Primary care doctor (PCP) or subspecialist is somewhat of a twilight zone. There is often no standardized way to determine the follow-up timeframe. For example, it may be reasonable that an otherwise healthy, 32-year-old patient admitted to the hospital for uncomplicated community-acquired pneumonia is recommended to follow up with their PCP within one week. At the same time, this recommendation for 1-week follow-up may sound more appropriate for a 72-year-old patient with underlying diabetes mellitus admitted for heart failure exacerbation.[1] In fact, for every high-risk patient who did not receive timely outpatient follow-up, a low-risk patient did.[2] Healthier patients may be better equipped to secure and attend an earlier follow-up appointment, but potentially at the cost of delaying care for those with more complex needs. The one-size-fits-all approach in transitional care planning is also taxing outpatient physicians. The shortage of physicians and growing concern by the Association of American Medical Colleges (AAMC) of further contraction of the physicians' pool by as much as 121,900 in 2032 necessitates implementing steps towards judicial discharge planning.[3,4]

There are different means to accomplish post-discharge follow-ups. It can be via a Tele-management program led by an advanced practice nurse for heart failure patients[5] and text messaging to surveil for post-operative pain and other complications as part of Enhanced Recovery after Surgery Program (ERP),[6] or therapy education for chronic diseases like diabetes.[7] Lastly, it can be a traditional, in-

person clinic visit with a primary care doctor or specialist. More or less, all these different means of follow-ups, when adequately carried out, had unanimously demonstrated an overall improvement in patients' medication compliance and quality of life and reduction in healthcare cost. A substantial proportion of these healthcare savings stemmed from a reduction in frequent hospitalizations.

The current interventions towards efficient healthcare focus on curtailing hospital readmission rates since nearly 90% of these readmissions are unplanned and potentially preventable, translating into \$26–44 billion or almost 20% of Medicare's hospital payments.[8] The Hospital Insurance (HI) part of Medicare which covers the in-hospital care cost for its beneficiaries, is facing the threat of inadequate funding due to projected depletion and insolvency of the trust fund by the year 2024. This dire situation might be made worse by the cuts in general tax revenue, which contribute almost half of the total program's funds.[9] With frail health of Medicare funds and the added burden of unplanned readmissions, the Centers for Medicare and Medicaid Services (CMS) introduced the Hospital Readmissions Reduction Program (HRRP), a value-based initiative to penalize hospitals for excess unplanned readmissions and to further incentivize hospitals towards improved post-discharge care coordination.

Multiple non-modifiable patient factors influence hospital readmission risk. Old age and high co-morbid burden in domains like cardiovascular, neurological, hepatic, and oncology domains contribute to a high Charlson Comorbidity Index. This, along with the extended length of hospital stays and multiple prior hospitalizations, is associated with significantly increased odds of 30-day readmission.[10] Simultaneously, the literature is rampant with evidence highlighting the inverse relationship between timely post-discharge follow-up with a primary care doctor and 30-day hospital readmission risk-be the primary hospitalization indication being heart failure exacerbation or high-risk surgery.[11–13] Of note, almost 50.2% of the patients rehospitalized within 30 days after a medical discharge had no reported visit to a physician's office in the period between discharge and rehospitalization.[14] In fact, of the ten domains of the Ideal Transition of Care (ITC) Framework, domains about advanced care planning and information transfer to receiving clinicians had a minimal representation. Only a few discharge interventions meeting these domains' descriptions having been implemented and studied in the literature.[15] Meanwhile, although The ITC framework comprises ten domains, timely post-discharge follow-up with PCP has the distinct power to potentially consolidate and reinforce both the pre-discharge domains and bridging domains of ITC framework.[16]

In the backdrop of gradually depleting Medicare's assets, the literature demonstrates the remarkable effectiveness of timely post-discharge follow-up in reducing hospital readmissions. However, it is imperative that discharge planning considers impending physician shortages such that earlier and emergent post-discharge follow-ups are reserved for sicker patients. Thus, the most critical step in making this intervention of timely post-discharge follow-up successful is accurate risk-stratification of the patient population. One effective tool for readmission risk profiling would be a clinical risk prediction model with a reasonable discriminative ability in identifying high-risk patients.

Different clinical readmission risk prediction models have been developed globally. These included patient and disease-specific parameters like specific medical diagnosis and illness severity, prior use of medical services, and social determinants of health.[17] A few prediction models incorporate variables like sociodemographic factors, such as drug use, housing discontinuities, access to healthcare, and functional status, which have fared better in accurately predicting admission risk. Thus when compared with the models which rely only on administrative variables, social patient-level factors add incremental value in predicting readmission risk.[18–20] In fact, of the total variation in the risk of readmission among hospitals, differences in patient characteristics, including race, gender, and nursing home residence, account for over half of the variation, as compared to only 0.08% of total variation explained by measurable hospital characteristics.[21] These patient-level factors also explain the success of a prediction model in one population. At the same time, it lacks success when applied to another population since social determinants may disproportionately influence readmission risk in socio-economically disadvantaged populations, even when the medical co-morbidities being studied are the same. Hence, developing an institution-specific prediction model that incorporates medical, administrative, sociodemographic, and functional variables may be the first step towards providing clinically relevant readmission risk stratification. It will also be beneficial for assigning appropriate risk-concordant timing for post-discharge follow-up and for triggering appropriate institution-specific transitional care initiatives, such as transition coach or a nurse discharge advocate.

Essentially, the proposed framework for developing a hospital-specific readmission risk model will involve retrospective chart review of patients readmitted to the same hospital within 30 days of discharge and extracting relevant data spanning administrative variables like discrete Clinical-risk groups, diagnosis-related groups, the severity of the chronic condition, and additional determinants like socioeconomic demographics and functional status. A skilled statistician will combine all the available information for each patient and builds a statistical model and index derivation tool to predict readmission (to the same hospital). After an initial run of internal validation, the model will be applied to new patients admitted to the hospital to predict the readmission risk and further prognosis assessment.[22] Also, the models need not account for readmission risk predictions of all patients but the highest-risk, condition-specific subset for whom the hospital plans specific initiatives. In earlier studies, hospital-specific readmission risk prediction models developed this way have outperformed LACE, a simple yet effective readmission risk-profiling tool.[19,22] Although it may be argued that potential data from patients readmitted to a different hospital from the one being studied will not be adequately accounted for when using single-site data, yet it should be noted that 80% of readmissions occur at the same hospital, possibly offsetting any bias.[23] However, in foreseeable future, significant proportion of the remaining 20% readmission could possibly be identified when different hospital systems catering to same state amalgamate readmission data, with each patient allotted unique identifiers. Such rich databases will promise consistency by virtue of data size and identify distinct regional health and socio-economic determinants associated with readmission.

This highly predictive, hospital-specific readmission risk prediction model may be utilized towards risk-concordant transitional care planning, involving earlier outpatient follow-up for patients with high readmission risk. Post-Discharge follow-up timeframe optimized this way will prevent significant strain on outpatient physicians and ensure equitable resource prioritization. The hospital administration, enticed by the promising potential of these predictive models, may fund the development and implementation of these prediction models and aim to ameliorate the socioeconomic risks and debilities associated with high readmission rates pertinent to their catered population, which, as evident in literature, tend to be the main locus determining excess readmissions compared to the hospital itself. The CMS may offer reimbursement and financial incentives to hospitals for implementing these technological innovations and patient-level interventions when they yield a reduction in readmissions.

No predictive model promises complete predictive accuracy. As more sophisticated machine learning algorithms are incorporated into health system information in the foreseeable future, and hospital records become more thorough with documentation of variables like socioeconomic factors, the predictive accuracy of these models will improve. Even after this lengthy endeavor, for an appropriately timed outpatient follow-up, recommended by the hospitalist at time of discharge, yield any reduction in readmission rates, the follow-up completion is a pre-requisite that further depends on multiple logistics like social support self-management skills, and resources.

Another potential hurdle to the completion of timely follow-up will be coordinating with outpatient physicians to see sicker patients post-discharge on short notice when they may not have the available scheduling space to accommodate these patients within the ideal timeframe. Likewise, it may be financially straining for these outpatient physicians to leave empty slots in their schedule to accommodate potential sicker discharge patients. Therefore, unless incentivized and judiciously reimbursed by National Health agencies and insurance companies, there may be little incentives for the outpatient physician to implement such measures.

Nevertheless, for physicians like us, while entering the era of accountable care practices, there is an ethical duty to use available technology, innovations, and information for implementing evidence-based approaches towards targeted resource allocation for overall benefit across the population, even if the question at hand is as simple as determining the appropriate timing for outpatient follow-up.

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Conflict of interest

The authors report no conflict of interest.

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