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The Role of Readmission Risk Assessment in Reducing Potentially Avoidable Rehospitalizations

By Omar Hasan, MBBS, MPH, FACP

Readmission to the hospital within a few days of discharge can be disconcerting to patients and may be linked to inadequacies in care delivery during transition from the hospital.[1,2] In recent years, increasing payer interest in curtailing payments for early rehospitalization and the advent of public reporting of 30-day readmission rates have prompted providers across the country to focus on finding ways to reduce potentially avoidable hospital readmissions.[3,4] Although broad-ranging improvements in the quality of care delivery during transitions will likely be necessary to achieve tangible reductions in early rehospitalization, the scarcity of resources in most health care systems will dictate that initial efforts be focused in areas of highest potential impact.

One feasible approach to maximizing the efficiency of quality improvement (QI) efforts in this area is to identify patients at high risk for readmission and selectively target care coordination resources to this subset. Such an approach is appealing because it permits focusing scarce resources where the impact may be greatest, provides a starting point for organizations struggling to find a focus amidst the myriad of choices for directing QI efforts, and allows for piloting robust models of transitional care delivery that can subsequently be expanded to include patients at progressively lower thresholds of readmission risk. Integral to this approach is the thoughtful selection and suitable application of appropriate readmission risk prediction models.

Readmission Risk Prediction

Readmission risk prediction is predicated on the logic that the presence of certain individual characteristics can prospectively identify a subset of patients at higher-than-average risk of early rehospitalization. The application of regression analysis to large inpatient databases has made it possible to delineate the relationship between pertinent patient characteristics and time-limited readmission risk in a mathematical formulation that can form the basis of a simple risk scoring system. Such risk prediction models or scoring systems can be used to develop a practicable framework for readmission risk assessment.

A high degree of *accuracy* in predicting the outcome of interest and a high level of *precision* in replicating predictive accuracy across relevant populations are the 2 key attributes of a valid and reliable risk prediction model. Accuracy of prediction is inversely related to how restrictively the outcome is defined; thus, it is harder to accurately predict the likelihood of 30-day readmission versus a *combined* outcome of 30-day readmission, or emergency department visit, or death. Precision depends, in part, on how closely the population to which the risk prediction model is being applied resembles the sample population used to derive the model. Both accuracy and precision are affected by the selection of appropriate patient characteristics for inclusion in the model building process (ie, whether these characteristics are representative of the majority of causative factors thought to be responsible for substantially increasing readmission risk in the population under consideration).

One of the key challenges in finding an appropriate readmission risk prediction model for use in QI efforts is selecting the most suitable model from among the multitude of condition-specific, as well as generic (ie, applicable to general medical or surgical patients), risk prediction models in the published literature.[5-10] One must consider 3 questions before making such a decision:

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(1) Are QI efforts currently focused on specific patient populations (eg, heart failure or pneumonia patients), in which case the most suitable condition-specific model should be sought?

(2) Are the data elements in the model readily available from existing clinical and/or billing information systems?

(3) Are the organization's frontline care providers – who will be responsible for using the model – likely to believe in its integrity and usefulness?

For the sake of brevity, the remainder of this article will focus on generic risk prediction models for adults, because these are applicable to a larger population of hospitalized patients than most condition-specific models.

As can be expected, results of regression analyses of several large hospital databases reveal that the strongest generic predictors of rehospitalization include: the number of prior hospitalizations or emergency department visits, the presence of multiple comorbid illnesses, and hospital length of stay (a proxy for severity of illness).

Two recently developed generic models deserve mention because of the simple and easily used risk scoring systems they have devised. Walraven and colleagues were successful in creating a simple risk scoring system through logistic regression analysis of patient characteristics in a multihospital database of 4812 medical or surgical discharges from 11 Ontario, Canada, hospitals (6 university-affiliated and 5 community hospitals).[9] Nursing home residents and cognitively impaired patients were excluded from this analysis. Four patient characteristics were found to be significantly predictive of death or unplanned readmission within 30 days of hospital discharge: hospital length of stay ("L"), acuity of the index admission (ie, emergent admission; "A"), comorbidities (measured with the Charlson comorbidity index; "C"), and prior emergency department use (number of visits in the previous 6 months; "E").

To facilitate recall of these 4 elements, the model was titled using a simple mnemonic, "LACE," and referred to as "the LACE index." This model was externally validated in a random sample of 1 million medical or surgical discharges from all Ontario hospitals (between April 2004 and January 2008) and found to perform reasonably well, with the median absolute difference between expected and observed 30-day death/readmission rates being only 1.6% (range 0.04% to 6.6%).

Hasan and colleagues also used logistic regression analysis to create a simple 30-day readmission risk prediction scoring system using a multihospital database of 10,946 home discharges from the general medicine services of 6 US academic medical centers; patients who died within 30 days of discharge were excluded from this analysis.[10] Seven patient characteristics were noted to be significant predictors of unplanned hospital readmission within 30 days of discharge: health insurance status (other than private insurance), being currently married, having a regular physician, Charlson comorbidity index, Short Form-12 physical component score, prior hospital admission(s) within the last 12 months, and hospital length of stay (of longer than 2 days). Points were assigned to each predictor and score cutoffs were determined to identify 5% of patients with an approximately 30% or higher risk of readmission within 30 days of discharge. Whereas 6 of the 7 predictors were positively correlated with a high readmission rate, having a higher physical function score on the Short Form-12 questionnaire was negatively associated with readmission risk for self-evident reasons.

A Comprehensive System for Assessing Readmission Risk

Although daunting in itself, selecting and deploying a regression-based readmission risk prediction model is only the first step toward realizing the full potential of readmission risk assessment in reducing potentially avoidable rehospitalizations. Despite the availability of robust statistical models for predicting readmission risk, risk assessment has yet to become a routine part of the health care delivery process across many provider organizations. This is largely attributable to the difficulty in linking model-predicted readmission risk with available risk reduction interventions.

There are 3 salient reasons for this implementation gap. First, risk prediction models, although useful as tools for selecting a high-risk subset of patients, are not user friendly for frontline clinicians such as bedside nurses, hospitalists, case managers, or discharge planning nurse specialists. There are 2 dimensions to this issue: not only are many risk prediction models suboptimal in categorizing patients into easily understandable low-, intermediate-, and high-risk categories, they are also poorly integrated into the current tools and workflow of frontline clinicians.

Second, because regression-derived models are designed to be parsimonious, key patient characteristics that may be actionable (eg, the need for help with executing discharge care instructions) are excluded from the final versions of most models as a result of their seemingly lower predictive power when compared with variables such as prior health care utilization. Unfortunately, a high score on a variable such as prior health care utilization isn't easy for frontline caregivers to link with a concrete choice of intervention such as a postdischarge phone call or arranging visiting nurse services.

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Third, the evidence demonstrating effectiveness of interventions for mitigating readmission risk has only begun to grow in recent years and, in most cases, frontline caregivers will have to continue to rely on a combination of evidence-driven interventions and their own best judgment in assigning interventions for the next few years.

It follows from the aforementioned that, in order to hardwire readmission risk assessment into clinical workflow and achieve measurable reductions in potentially avoidable early rehospitalizations, organizations will need to focus efforts on developing a comprehensive system for readmission risk assessment. Such a system should not only emphasize selection of the most appropriate risk prediction model but also address salient causes for the implementation gap cited previously. Risk prediction models should be integrated into tools that are currently used to assess patients' discharge needs and systematically assimilated into everyday clinical workflow through an iterative process of sequential plan-do-study-act cycles.

Additional questions directed at assessing the need for particular risk reduction interventions should be added to risk prediction scoring systems in order to devise hybrid tools that combine risk prediction with a template for matching patients to appropriate interventions that target the risk elements identified.

In designing pathways for linking interventions to patients, frontline caregivers should be allowed flexibility in selecting interventions, taking into consideration the uncertainty that exists about the effectiveness of known interventions in the published literature. Lastly, organizations should seek to maximize utilization of existing programs and resources through adoption of such a comprehensive risk assessment system before embarking on efforts to devise new programs or interventions.

Conclusion

Readmission risk prediction holds great promise as a tool to focus efforts to reduce potentially avoidable rehospitalizations. Key to realizing its full potential are appropriate model selection, integration into existing tools and workflow, and ensuring appropriate linkages with risk reduction interventions. Despite these challenges, effective use of a comprehensive system to assess readmission risk is an essential step toward successful implementation of an organization-wide strategy aimed at saving costs through measurable reductions in 30-day rehospitalizations.

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