Predictive Analytics: Models to Cut Readmissions

by Jennifer Maybin

For decades, hospitals have been looking for ways to better target resources toward patients at highest risk for readmission. With the Centers for Medicare & Medicaid Services (CMS) enforcing cuts in reimbursement for three chronic disorders – heart failure, acute myocardial infarction and pneumonia – beginning Oct. 1, there’s a heightened sense of urgency to reduce 30-day readmissions.

Predictive analytics, a statistical technique that uses modeling and data mining to identify trends, can help. Although predictive modeling alone cannot reduce rehospitalizations, this approach can be used to calculate which patients are at greatest risk for readmission. Unfortunately, predicting risk for readmission is not so simple. That’s because readmission risk depends not only on inpatient environments with relatively manageable variables but also on outpatient environments where variables are beyond hospital control.

Some hospitals are currently targeting the three disorders named by CMS, whereas others are taking a broader approach. Predictive analytics is the tactic many are using.

Pilot Focuses on CHF Readmissions.
At NorthShore University HealthSystem, predictive analytics are being used to predict which heart-failure patients are at highest risk for readmission. Ari Robicsek, MD, vice president of clinical and quality informatics and associate chief medical information officer of the Evanston, Ill.-based health system, explains that "retrospective data from several thousand heart failure patients’ electronic medical records were used to create our initial model. From the literature, we identified hundreds of variables that affect heart failure outcomes and narrowed our choice to 35 in building our pilot predictive model using logistical regression techniques." These variables include, for example, the number of times a patient had been admitted and specific medications.

NorthShore’s predictive analytics test model segmented patients into quartiles. Those in the top quartile were considered to be at high risk; the middle two quartiles, medium risk; and the bottom quartile, low risk. Validation of the model over several months, during which aggressive interventions were not used to change outcomes, showed that low-risk patients were readmitted at a rate of 12 percent; medium-risk, 16 percent; and high-risk, 33 percent.

"We then began a pilot program to test the model," continues Dr. Robicsek. "The data entered into patients’ EMRs each day feeds into the predictive modeling tool, which calculates daily risk, based on the algorithm we created. We’ve implemented an alert system whereby an e-mail is sent each morning to staff in a variety of departments where the model is being piloted. The e-mail identifies each hospitalized heart failure patient according to high, medium, and low risk." The clinical staff then intervenes with individual patients based on their risk on each day of hospitalization and determines appropriate interventions post-discharge.
“No two CHF models are going to be the same,” Dr. Robicsek explains. “The most important variables in predicting risk in our population were the number of previous admissions, the number of medications, and the type of medications, as well as several laboratory results. Comorbidities did not end up on our final list of variables in this current model, but for another organization, that variable may be important.”

Targeting All At-Risk Patients.
About a year ago, Indiana’s Community Health Network began to use predictive analytics to help reduce readmissions, according to Deborah J. Lyons, MSN, RN, NE-BC, integration network diseases management executive director. Rather than focusing specifically on heart failure, the health system sought to develop a tool to identify all patients at risk, says Lyons, who wrote the project plan.

Community Health started with LACE, a tool that calculates a readmission risk score based on length of stay (LOS), acute admission through the emergency department (ED), comorbidities and the number of emergency department visits in the past six months. The health system found that LOS was not helpful in predicting readmission because it calculated risk at discharge rather than early in the hospitalization, when the clinical staff can still intervene. It tossed the “L” in LACE and settled on an ACE score (using LACE’s final three variables). ACE, Lyons says, “gives the hospital tremendous advantage in identifying patients at risk on admission.” About 10 percent of all patients admitted are identified as at-risk for readmission.

Once these high-risk patients are identified, the health system implements additional assessments, carried out by a transition nurse case manager, that provide staff with details of what to focus on and why. “The additional assessments provide information for the health-care team on how to develop a plan that targets a patient’s specific risk factors, whether those risks are clinical or socioeconomic or environmental,” explains Lyons. The first two months of data will be analyzed over the next few months.

Environment Variables Part of Mix.
What is essential in these predictive analytics models is that variables are included to identify risk factors for patients specific to each health system’s population. Inpatient variables are fairly homogeneous across hospitals. But outpatient variables, which particularly affect readmission risk, can be quite heterogeneous.

For example, factors that affect readmission risk for patients in the inner city may not be relevant for patients in rural communities. Variables differ according to the relative wealth of patient populations, the available community resources, and the presence or lack of family and community support systems. Therefore, information fed into predictive analytics models that pertains to readmission risk must include data about the patient’s environment outside the hospital’s four walls.

Importantly, at both Community Health and NorthShore, the information captured from the predictive analytics tools is shared with both inpatient and outpatient health-care providers. At NorthShore, the patient’s primary-care physician receives notification via e-mail of the patient’s discharge, his risk score and confirmation of whether a follow-up visit has been scheduled. “Our physicians are tremendously pleased with this system,” says Dr. Robicsek.

Capturing Health Behavior and Perception Variables.
Hospitals cannot rely on medical data alone to predict who is at high risk of readmission,
according to Julie A. Meek, PhD, RN, CNS, clinical associate professor at Indiana University School of Nursing. “Outcomes are very much dependent on patients’ health behavior and health perceptions,” Meek says. “Aftercare requires a lot of support from family, and there are numerous social predictors of what happens after discharge.”

Including such data in the predictive analytics model is, in fact, what Dr. Robicsek at NorthShore is working on with his team now. Although the health system’s initial pilot predictive analytics model included just 35 variables, the group is now investigating a model that incorporates 150 variables, including inpatient and outpatient variables that have been identified with the help of experts in the care of patients with heart failure.

As predictive analytics models evolve, it will be imperative for staff that cares for patients, those who develop programs that capture data, and those who build the tools that analyze data to work as teams to identify the variables that are most important to specific patient populations and specific diseases.

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