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Readmissions NEWS

Using Artificial Intelligence to Reduce Readmissions

by Sujay Kakarmath, MD MS and Kamal Jethwani, MD MPH

Reducing readmissions has been a formidable challenge and a top priority for many US hospitals since the inception of the Hospital Readmissions Reduction Program. Significant effort and resources have since been directed to developing multi-faceted interventions for inpatients determined to be at high-risk for readmissions. However, reduction in readmissions over the past 5 years has been modest at best. Considering the cost incurred in delivering resource intensive interventions to reduce readmissions, hospitals have been looking for ways to fine tune their efforts.

One of the lowest hanging fruits has been to improve the accuracy of risk prediction models used to identify high-risk patients. In the early years after implementation of HRRP, most hospitals went for simple approaches that were ideal for busy clinicians and used risk prediction models that required at most 5 variables to generate a risk score for every inpatient. This was not necessarily due to a dearth of more accurate risk prediction models.

More than 90 readmission risk prediction models have been developed and validated in the past three decades. Some of these use as many as 90 variables to generate a prediction score. Naturally, there has always been a trade-off between model accuracy and ease of implementation. This is by no means the only factor hospitals have had to consider when adopting risk prediction models. A second, seemingly innocuous problem, has been that of the timing of availability of data inputs required for risk prediction.

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In This Issue

SDOH in Reducing Readmissions – New perspective

by Anton Berisha, MD, and Kathy Mosbaugh

Background

The CMS' Hospital Readmissions Reduction Program (HRRP) has recently come under scrutiny as the progress in reducing readmissions and associated costs came to a standstill. As a result, about 75 percent of eligible US hospitals are being penalized with up to 3 percent cuts to their Medicare payments.

This reminds me of a conversation from a few years ago, when a CMO of a prominent academic medical center – while claiming that he has done everything possible from the clinical recommendations standpoint to curb the readmit rates – said he can tell if a patient is discharged and going back to certain neighborhoods, that chances of being readmitted within next 30 days are very, very high. At that time, we weren't able to measure or validate his assertion, but what is important is that his perception supported that social determinants of health (SDOH) may be a significant driver of 30-day readmissions even more so than clinical conditions.

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Editor's Corner

Greetings readers of *Readmissions News*! We are pleased to be bringing you another excellent addition of the newsletter. I would also like to thank our many contributors for their excellent insights into this most important of issues. As always, if you have any questions, comments or concerns or would wish to contribute an article to the newsletter please don't hesitate to contact me personally.

Kind Regards,
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For any risk prediction to be clinically actionable, it must be available soon enough from the moment a patient is admitted. Many of the traditional risk prediction models are not implementable for this reason alone. Another reality of the more traditional risk prediction models is that they have been developed using curated datasets with several steps taken to reduce bias, including that which results from missing data. However, missing data is a fact about today's hospital data. The already modest performance of traditional risk prediction models worsens substantially under real-life hospital conditions, where it is meant to be used. Use of curated datasets to develop models that are optimized to perform well in several patient populations also results in them not being optimized for a specific patient population. The result is a risk prediction model that will often provide the same risk score across hospitals irrespective of factors such as patient mix and quality of care provided.

Hospitals are learning from this experience and are increasingly looking at adopting machine learning based techniques to generate risk scores. This is not to say that the lack of earlier adoption was merely due to a lack of foresight. A major barrier to adoption was the lack of technological infrastructure- electronic medical records (EMR) in particular- required to support such an endeavor. As recently as 2008, the number of hospitals in the US that had a basic EMR system was less than 10%. Now, the number is close to 100%. This has created a wealth of opportunities to leverage the data captured in EMRs to generate risk prediction for an individual patient. For instance, at Partners Healthcare, we used deep learning to develop a 30-day readmission risk prediction model for patients with heart failure. This model was developed using data from about 30 thousand inpatient admissions, and uses information from more than 3000 variables to generate a risk prediction for a given inpatient admission. The beauty of this model is that it uses information from physician notes as much as from pre-defined structured variables to calculate the readmission risk.

> *"As recently as 2008, the number of hospitals in the US that had a basic EMR system was less than 10%. Now, the number is close to 100%."*

We are poised to gain several unique advantages in our efforts to reduce readmissions by using a machine learning based model. First, this model has been tailored to the population seeking care at Partners' hospitals, and provides a highly personalized risk score for every patient. Second, this model can generate a risk score at several time points during a patient's admission, allowing for early intervention in the index admission itself – why wait until after a patient is discharged?

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Third, this system is designed to be adaptable as Partners Healthcare evolves over time based on the insights obtained through the system. These capabilities could not have been imagined without the technological and computational advancements of our times.

We conducted a study to simulate the readmission prediction model among heart failure patients participating in the Partners Connected Cardiac Care Program (CCCP), a remote monitoring and education program designed to improve the management of heart failure patients at risk for hospitalization. These results were compared to data from approximately 12,000 heart failure patients hospitalized and discharged from the Partners HealthCare hospital network in 2014 and 2015. The analysis showed that, approximately, an additional US $7,000 savings per patient per year among the cohort of CCCP patients can be expected. We are now taking our efforts to the next level by incorporating a component to explain the reasons behind the prediction made by the algorithm. This will add a layer of qualitative nuance to the quantitative risk estimated by the algorithm, thereby enabling our care teams to act swiftly on personalized, patient-specific risk factors.

> *"...an additional US $7,000 savings per patient per year among the cohort of CCCP patients can be expected."*

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SDOH in Reducing Readmissions – New perspective...*continued from page 1*

The CMS' HRRP's perceived lack of progress has highlighted the fact that hospitals cannot control patients once they are released, and that SDOH may play a greater role in whether the patient is readmitted within the sanctioned timeframe of 30-days, or not. Recent studies claim that social determinants of health account for as much as 50 percent of health care outcomes. Among these outcomes, 30-day readmission probably is near the top of the list of events driving negative outcomes from both a clinical and financial perspective.

Yet, value-based care focuses on outcomes with "Readmissions within 30 days after discharge" as one of the outcome metrics. How do healthcare organizations address this gap?

There are discussions going on around alternative options: from trying to remove the program altogether, replacing it with other value-based care initiatives within CMS, or initiatives asking that HRRP measurements should be risk adjusted for SDOH.

New perspectives from LexisNexis® Risk Solutions Health Care

After working with many payer and provider organizations and completing validations of multiple data sources, there are several important factors to consider when approaching the problem of readmissions using SDOH:

1. **Access to personal, individual socioeconomic data.** It is good to have census tract, ZIP code or other regional level aggregated data on individuals, but you also need to know what is personally affecting an individual such as increases or decreases in income, whether they moved several times in the last 12 months, or how connected they are to others around them. In order to have a successful implementation of SDOH, you need both types of SDOH attributes.
2. **Access to a variety of socioeconomic attributes.** Just income or education alone, while very useful, can't give you the complete picture of somebody's socioeconomic environment. A combination of multiple data sources will give you the best picture on each individual: identity, addresses, housing, education, income, professional licenses, assets, car accidents, bankruptcies, crimes, evictions, sub-prime credit, relatives and associates, businesses, etc. These data must be reliably linked to a single record to ensure a holistic view of the individual which can then be associated to their clinical history.
3. **Access to clinically validated socioeconomic data.** Not all individual level data are created equal for forecasting future health risk. There is significant work needed to understand, clean up and select SDOH data that correlate and show significance relative to the risk of readmission or other health care outcomes. By using ***clinically validated SDOH attributes*** to score patients, you ensure that you have maximized the impact that SDOH data will have in developing algorithms.

> *"By using clinically validated SDOH attributes to score patients, you ensure that you have maximized the impact that SDOH data will have in developing algorithms."*

Let's consider a specific example of a SDOH attribute in relation to readmission as an outcome. In the graph below, you can see that the "Overall" columns on the right show that a change in a person's address in the last month doesn't have any impact on the probability of a 30-day readmission.

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