wide range of values over time and an equivalent number of outcome values in a regression model known as multivariate analysis of variance. The authors recognized the complexity of using continuous values of hemoglobin A1c, creatinine, and hematocrit in a prediction model and chose to model these 3 continuous variables with 2 discrete values before and after or during the operation. From a clinical standpoint, the authors' choice of modeling before and after the operation makes sense, although it might not be as rigorous as possible. Others have used similar modeling to study endocarditis.³

The fact that it is possible to predict readmission following cardiac operations with some degree of certainty leads to a logical extension that evaluates the means of limiting readmissions. As the authors point out, patients who stay longer in the hospital after an operation tend to have fewer readmissions. There is not much clarity about modifiable risk factors that can potentially limit readmissions.⁴ Discharge planning and patient education are suggested options to limit readmissions but with inconsistent

benefits. Patient characteristics explain only a minor part of readmission rates, and most patient factors associated with readmissions are nonmodifiable (eg, age).⁵ Thus, readmission after cardiac operations remains a rather perplexing complication of the procedure, but the addition of time-dependent predictors of readmission may stimulate further work in this area.

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See Article page 943.

Commentary: Readmission risk reduction and the new age of data integration

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On October 1, 2012, the Secretary of the Department of Health and Human Services established the Hospital Readmissions Reduction Program. In 2017, the program was expanded to include coronary artery bypass surgery in the penalty of reduced hospital reimbursement. The program has not been without its controversies. The risk model supporting the program has relatively poor discrimination¹; the decision to exclude socioeconomic factors in the modeling may have adversely impacted safety net hospitals²; and the

Impact of readmission reduction program on raw and adjusted readmission/mortality rates.³

CENTRAL MESSAGE

Regardless of one's perspective on readmissions, creative use of robust and integrative approaches to data acquisition and analysis will continue to improve the risk models of the future.

program may have actually resulted in a greater patient mortality.³

Central to these controversies is the ability to determine which readmissions might be avoidable. From the

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Department of Health and Human Services perspective, the goal is to evaluate how well institutions perform on comparable patients. Risk models focus on preadmission variables. However, from an institutional perspective, the goal might be to identify patients at greatest risk at any point before discharge to activate available resources for reducing risk of readmission.

In this realm, the study of Manyam and colleagues⁴ introduces several innovative approaches. First, their commitment to use all available data—both registry and medical record—not only helps to inform their modeling but alerts us a bright future of integrative data approaches to quality improvement and outcomes research. Several query languages were used to access and process this information. As the field of semantic logic continues to improve, one can easily envision increasing access to the vast storehouse of unstructured data that resides within the medical record. The merger of such data with genomic, proteomic, and metabolomic data sources combined with the prodigious processing power that drives the rapidly emerging techniques of artificial intelligence, will help to further inform and refine clinical risk adjustment and decision-making. Second, the authors' seamless merging of traditional statistical with machine learning approaches is certainly going to continue to improve our analytical capabilities.

The major thrust of their article is that inclusion of time-related variables improves predictive modeling. Integration of analytical techniques that can more clearly account not only for the level of a variable at different times but also the variations over time is an exciting proposition.

Perhaps the drop in hemoglobin from preoperative to lowest intraoperative level is more meaningful than either value in isolation. In addition, attention to time-dependency may relate not only to variables but to the timing of events. Current registry data permit us to study combinations of complications but not the impact of one complication on another.

The final issue raised by the authors' study is not so much whether their risk model can be more broadly adopted by other institutions but rather whether each institution can develop such program-specific models that can then be imbedded into the electronic medical record automatically generating an iterative risk score for patients as they progress through their hospital stay, at each point helping to alert the caregivers of what resources might be most appropriate to mobilize for each patient. Regardless of one's perspective on readmissions, such creative use of emerging data analytical tools is likely to help improve patient care.

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