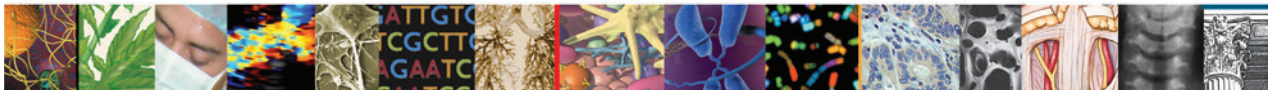

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Perspective

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Clinical and Social Risk Adjustment — Reconsidering Distinctions

Shantanu K. Agrawal, M.D., and William H. Shrank, M.D., M.S.H.S.

Careful risk adjustment is at the core of any equitable payment model for the care of populations. There is widespread agreement that U.S. health care providers and payers who are responsible for the care of sicker patients (and its cost) should be compensated more generously than those who are responsible for the care of healthier patients, to limit perverse incentives that would encourage providers to selectively care for healthier patients. For years, Medicare has used rigorous risk-adjustment methods that account for various clinical characteristics to adjust population-based payments for Medicare Advantage plans and for health systems and clinicians participating in risk-based arrangements. Such methods are also applied in value-based arrangements, under which reimbursement is altered on the basis of patient outcomes in defined areas. The most common characteristics used for clinical risk adjustment include age, sex, surgical history, and conditions such as heart disease and diabetes.

With the growth of value-based purchasing, there has been increasing concern that clinical risk-adjustment methods are insufficient. A community's resources — such as safe environments for exercise and stores that sell healthy and fresh food — and patients' access to those resources substantively influence the outcomes on which clinicians are judged. Patients who are socially isolated, experience housing instability or food insecurity, and have limited transportation options have been consistently shown to have worse health outcomes than other patients, even when appropriate health care interventions are prescribed or recommended.[1] Some evidence shows that performance-based reimbursement programs penalize or reduce payments to providers who care for socially disadvantaged people,[2,3] which suggests that existing risk-adjustment methods don't sufficiently address social context.

As a result, a number of clinicians, researchers, and policymakers have advocated for risk adjustment that explicitly accounts for social characteristics. The goal is to level the playing field by providing clinicians with the necessary resources to care for more vulnerable patient populations. Without question, there are strong relationships between some social characteristics, health outcomes, and resulting health care costs. Researchers have consistently found that considerable variation in health outcomes and costs is accounted for when social

factors are added to risk-adjustment models that include clinical characteristics.[3,4] Incorporating neighborhood characteristics and other variables that capture social context into risk-adjustment models has been shown to improve cost estimation and can be feasible; however, it creates a new set of challenges, such as the need for new data sources.[2,4,5]

Yet there is considerable controversy regarding this type of risk adjustment. Consumer and patient advocates and employers, among others, have expressed concern that social risk adjustment may be perceived as lowering the standard for quality of care for socially disadvantaged populations. By adjusting for patients' social characteristics, the risk-adjustment models would apply what amounts to a "credit" to clinicians who care for the most socially disadvantaged patients — thereby obscuring these patients' poorer outcomes. Some institutions, including the Centers for Medicare and Medicaid Services (CMS), have struggled with the optics of a payment model that implicitly acknowledges any inequity in expected outcomes based on social characteristics. One compromise approach has been to distinguish risk adjustment of performance on quality measures and processes of care from risk adjustment of payments to clinicians. In keeping with this compromise, the 21st Century Cures Act requires CMS to stratify readmission measures by patients' dual-eligibility status but doesn't include an associated payment adjustment.

Despite differences in the ways in which clinical and social risk factors are managed in various quality-assessment and payment programs — and the health care system's relative comfort with clinical risk adjustment — we question whether the distinction is indeed so clear. Accumulating evidence would suggest that clinical and social risk factors overlap far more than has previously been conceptualized. For example, the diagnosis of a chronic disease such as diabetes is commonly included in clinical risk-adjustment methods, yet both rates of diabetes and outcomes in patients with diabetes have been linked to social and neighborhood characteristics such as poverty and education.[1]

Even age is thought of as an immutable predictor of risk and is usually included in clinical risk-adjustment methods. An analysis of performance measures endorsed by the National Quality Forum (where one of us is president and CEO) showed that of 193 measures for which a risk-adjustment model was employed, 89% had models that used age as a variable. Even safety measures and measures specifically designed for geriatric patients adjust for age. Yet age most likely affects health outcomes by means of various biologic and nonbiologic mechanisms, which include higher rates of poverty, social isolation, and food insecurity among older people.

Despite the accepted framing of risk adjustment, in reality our approach to accounting for clinical risk probably embeds social risk, owing in no small part to an oversimplification of disease processes and burden and an insufficient understanding of the ways in which social context affects disease burden. We believe the consternation that surrounds accounting for social factors in risk-adjustment models is too myopic; it should make us uncomfortable with the integrity of the concept of clinical risk and should highlight the need to better characterize differences between these ideas. As we continue to progress toward population-based payment models, we hope and expect there will be even greater emphasis on fostering early interventions for various disease processes, with the goal of preventing disease and keeping patients healthy. In this setting, the line between clinical and social risk will only blur further. Efforts to reduce the incidence of diseases such as diabetes and hypertension should account for social context and disproportionately target people at greatest risk — members of the population who face social challenges to forestalling or managing these conditions.

We believe it is time for a meaningful reconsideration of the goal of, and approach to, risk adjustment writ large in quality measurement and payment systems. The discussion should no longer be about the dichotomy of clinical risk versus social risk. If our goal is to align payment with the outcomes we hope to produce, we should acknowledge the interdependence of social, behavioral, and physical domains in constituting risk and producing better health. Current risk-adjustment models assume these factors exist in isolation, include some factors while excluding others, and fail to capture social context explicitly and intentionally. The best approach may be to discuss how to provide appropriate resources to clinicians, taking into account all types of risk in the populations they serve. We could also determine how performance data can be presented to stakeholders, including the public, so that it genuinely acknowl-

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edges gains while being clear-eyed about populations who don't benefit from those gains. Adopting methods that account for all factors that influence risk, and for the interdependence of those factors, could be an important step in creating a more equitable health care payment system that better serves patients, including the most disadvantaged members of society.

An audio interview with Dr. Shrank is available at NEJM.org

Disclosure forms provided by the authors are available at NEJM.org.

From the National Quality Forum, Washington, DC (S.K.A.), and Humana, Louisville, KY (W.H.S.).

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Prediction Models — Development, Evaluation, and Clinical Application

Michael J. Pencina, Ph.D., Benjamin A. Goldstein, Ph.D., and Ralph B. D'Agostino, Ph.D.

When national lipid guidelines first incorporated a model based on data from the Framingham Heart Study — a turning point for the role of risk prediction in health care — that Massachusetts city was an anomaly: a community with extensive, available, longitudinal health data. Today, U.S. health care systems have amassed large, local data sets through adoption of electronic health records (EHRs) and the standardization associated with provider consolidation. More recently, payers have moved toward capitation and other value-based models. This shift places a higher premium on avoiding costly conditions altogether. These trends create greater demand for prediction models, since prevention is difficult without accurate identification of who specifically is at risk.

Prediction models' newfound importance and the emergence of model development based on machine learning raise questions about how to ensure their safety and efficacy, given their growing role in risk stratification, care pathways, and clinical outcomes. A systematic review comparing clinical prediction models based on regression with those based on machine learning revealed troubling weaknesses in model evaluation.[1] Given the number of emerging prediction models and their diverse applications, no single regulatory agency can review them all. This limitation, however, does not absolve models' developers and users from applying the utmost scrutiny in demonstrating effectiveness and safety. It also highlights the need for accepted standards for development, evaluation, and application of prediction models.

Fortunately, foundational principles for model creation and use have emerged.[2,3] These principles will have to be adapted and augmented for current conditions, which include new sources of data. We offer eight key considerations for the introduction and use of prediction models (see table for illustrative examples).[4,5]

1. Population at risk: Correct identification of persons at risk and the time when the model will be applied to inform intervention strategies is critical. Such identification requires a focus on the demographic characteristics, health status, and location of the patient population as well as on the clinical context in which a model will be used. The pooled cohort equations that drive current cholesterol guidelines, for example, are based on persons without atherosclerotic cardiovascular disease (ASCVD) who are 40 to 79 years of age and not currently receiving lipid-lowering treatment. Consequently, these equations should not be applied to people with a history of ASCVD, people currently taking lipid-lowering treatment, or people under 40 or over 79. Including broad swaths of the population who are at very low risk (e.g., women in obstetrics units) in a model for determining sepsis risk can make it harder to identify people with genuinely high risk. The