Landy et al1 addressed racial inequities in lung cancer screening recommendations. Under current recommendations, patients must have sufficient life expectancy to warrant screening. The Life-Years from Screening-CT (LYFS-CT) model recommended by the American College of Chest Physicians to identify screening candidates incorporates estimates of overall life expectancy and lung cancer mortality based on patients' race and ethnicity. Afircan American individuals have lower life expectancy and higher cancer mortality than White populations, likely due to disparities in environmental, social, or behavioral factors that impact health outcomes. As a result, the LYFS-CT recommends fewer screenings for minoritized individuals compared with White patients with similar age and other characteristics. While the LYFS-CT model may be defensible from a statistical perspective, it is unacceptable from a social perspective if it exacerbates existing disparities. Landy et al1 proposed a counterfactual approach that uses the current LYFS-CT model but substitutes the life expectancy or cancer mortality for White individuals to estimate life expectancy and cancer mortality for individuals from minoritized groups. This innovative approach to risk estimation preserves statistical integrity while simultaneously addressing social inequities.

Prediction models derived through statistical rigor are increasingly used to assist clinical decision-making. As the article by Landy et al1 highlights, blind adherence to statistical precision to support clinical decisions may result in recommendations that are incongruous with societal goals. In particular, decision models constructed with the goal of identifying patients most likely to benefit from health interventions have an endogeneity problem: the predicted benefit of an intervention may be lower for patients from racial and ethnic minority groups than for other patients, but the lower benefit is itself due to past inequities in the availability of health and other social interventions.

Historically, classification of humans by race or ethnicity has been used to impose hierarchies in society—often with the inaccurate suggestion that individuals from racial and ethnic minority groups are genetically inferior. In reality, the human race is strikingly homogeneous, with 99.5% to 99.9% identical genome across the species.2 While there is evidence that genetic variations by ancestry (rather than race) may be related to some health conditions,2 most differences in health outcomes by race or ethnicity are explained by disparities in social factors such as housing insecurity, financial, diet, and behavior, many of which are the legacy of past political, legal, or economic policies.3 Unfortunately, data representing these underlying phenomena are typically unavailable to clinicians, who therefore rely on race or ethnicity as a proxy. This is problematic for multiple reasons. First, as depicted by Landy et al,1 is the possibility that using race or ethnicity for clinical decisions may actually exacerbate existing disparities. Second, race and ethnicity do not cause health outcomes but are only correlated with health. Third, measurement of race itself is problematic. Race is typically treated as categorical, which does not reflect the diversity within communities of color or multiracial individuals.

This dilemma leads to the question: When is it appropriate to consider race or ethnicity in clinical decision models? Omitting factors that improve prediction accuracy can lead to model misspecification, but improving statistical precision is not a sufficient reason to use race or ethnicity in clinical prediction without sound rationale. Guidance to tackling this dilemma may be found in the age-old dictum: Do no harm. Essentially, risk models should not reduce the likelihood of appropriate care because of an individual's race or ethnicity but should recognize race or ethnicity when to do so.

Open Access. This is an open access article distributed under the terms of the CC-BY License.
improves the likelihood of appropriate care. As an example, Landy et al. proposed that recommendations for lung cancer screening should never be downgraded under the counterfactual approach. In another example, in 2021, the joint task force of the National Kidney Foundation and American Society of Nephrology recommended removing race from glomerular filtration rate estimation, an important criteria for diagnosing chronic kidney disease. Prior to this revision, the estimated glomerular filtration rate would be higher for a Black patient compared with a White patient with identical age, sex, and weight, resulting in delayed chronic kidney disease diagnosis and fewer treatment referrals for Black patients.

In contrast, failure to consider race or ethnicity may result in lower assessed risk than appropriate in some cases, leading to inadequate treatment. For example, the well-known Framingham Risk Score quantifies coronary heart disease risk in adults but has questionable generalizability to Black populations. Underestimation of risk in Black populations delays the provision of effective prevention such as statins. In contrast, the newer atherosclerotic cardiovascular disease risk calculator incorporates race (Black, White, or other) and has been shown to perform better than the Framingham Risk Score at predicting 10-year atherosclerotic cardiovascular disease risk as well as subclinical vascular disease. Nevertheless, race and ethnicity are rarely included as predictors in clinical risk models even in conditions for which it is known that minority individuals have higher risk. The reluctance to include race in clinical risk models is understandable, given that the use of racial profiling in other contexts is clearly inappropriate (eg, law enforcement). However, in the medical context, there are harms for both underestimation and overestimation of risk. Under the do no harm doctrine, adding race or ethnicity to clinical prediction models should be undertaken only with full consideration of the impact on those populations and with an understanding that race serves primarily as a proxy for factors that we cannot always measure.

It is also worth noting that risk models to identify candidates for disease screening typically do not consider outcomes other than the risk of disease, ignoring the possibility that consequences of disease differ by race. For example, the estimated risk of breast cancer is lower for Black women compared with White women with similar characteristics, yet Black women are 41% more likely to die from breast cancer compared with White women. To better reflect racial differences in disease risk as well as survival, it may make sense for screening prediction models to incorporate composite outcomes reflecting the risk of disease as well as consequence of the disease when it occurs.

This era of advanced analytics holds much promise for improving the provision of individualized medicine through better prediction. Greater understanding of social risk factors that impact health as well as increased screening for social risk factors and capturing data to reflect these factors will likely improve future clinical risk prediction. In the meantime, clinicians and researchers must be cognizant of the unintended consequences of clinical decision tools as we grapple with how best to consider the unique needs of socially vulnerable populations.
REFERENCES


