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Algorithmic fairness in cardiovascular disease risk prediction: overcoming inequalities

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ABSTRACT

The main purpose of prognostic risk prediction models is to identify individuals who are at risk of disease, to enable early intervention. Current prognostic cardiovascular risk prediction models, such as the Systematic COronary Risk Evaluation (SCORE2) and the SCORE2-Older Persons (SCORE2-OP) models, which represent the clinically used gold standard in assessing patient risk for major cardiovascular events in the European Union (EU), generally overlook socioeconomic determinants, leading to disparities in risk prediction and resource allocation. A central recommendation of this article is the explicit inclusion of individual-level socioeconomic determinants of cardiovascular disease in risk prediction models. The question of whether prognostic risk prediction models can promote health equity remains to be answered through experimental research, potential clinical implementation and public health analysis. This paper introduces four distinct fairness concepts in cardiovascular disease prediction and their potential to narrow existing disparities in cardiometabolic health.

INTRODUCTION

Health equality, defined as the fair and equitable distribution of health resources and opportunities to all members of a population, is a fundamental principle embedded in EU laws and directives; these laws prohibit discrimination based on sensitive attributes, such as sex, gender, race, ethnicity and socioeconomic status. While cardiovascular diseases (CVDs) impose a significant burden on healthcare systems, health inequalities themselves also carry tremendous direct and indirect costs. In the EU, it has been estimated that health inequalities account for 20% of total healthcare costs, and result in nearly 1 trillion EUR in welfare losses per year.[1] Despite progress in reducing these inequalities, large disparities in CVDs still exist between and within EU countries.[2–4] Research has shown that these disparities are closely linked to socioeconomic and sociodemographic factors such as income security, social protection, living conditions, human capital, quality of healthcare and working conditions.[5] The association between socioeconomic factors and CVDs is large and has been robustly established.[6–9] In addition, these factors disproportionately affect minority and immigrant populations,[10] highlighting the need for targeted interventions to address these underlying causes and promote health equality.

False equality: algorithmic unfairness in CVD prediction

Prognostic risk prediction algorithms for CVDs have proven to be valuable tools in identifying individuals at high risk,[11 12] allowing for early preventive interventions.[13] This approach is in line with the principle of precision medicine, which aims to allocate resources to those who are most at risk. In the EU, the Systematic COronary Risk Evaluation (SCORE2) and the SCORE2-Older Persons (SCORE2-OP) algorithms are currently the standard for predicting an individual's 10-year risk of developing CVDs.[11] However, these models only include biological determinants of CVDs (age, sex, blood pressure and lipids) and smoking status as a lifestyle factor, and do not take into account socioeconomic determinants of CVDs, which have been shown to contribute to significant within-country disparities in cardiovascular health.[2] As a result, the SCORE2 algorithms, which have been calibrated to perform well on average in four distinct risk regions in Europe,[11] are likely to overpredict the risk of CVDs in individuals with higher socioeconomic status and underpredict the risk in those with lower socioeconomic status. This can lead to a further widening of existing disparities, as those with lower socioeconomic status will be allocated fewer healthcare resources and those with higher socioeconomic status will be allocated more resources (figure 1). Such underestimation of CVD risk by the SCORE2 algorithm in those socioeconomically deprived has been experimentally demonstrated.[14] Recently, a large epidemiological study of 155 000

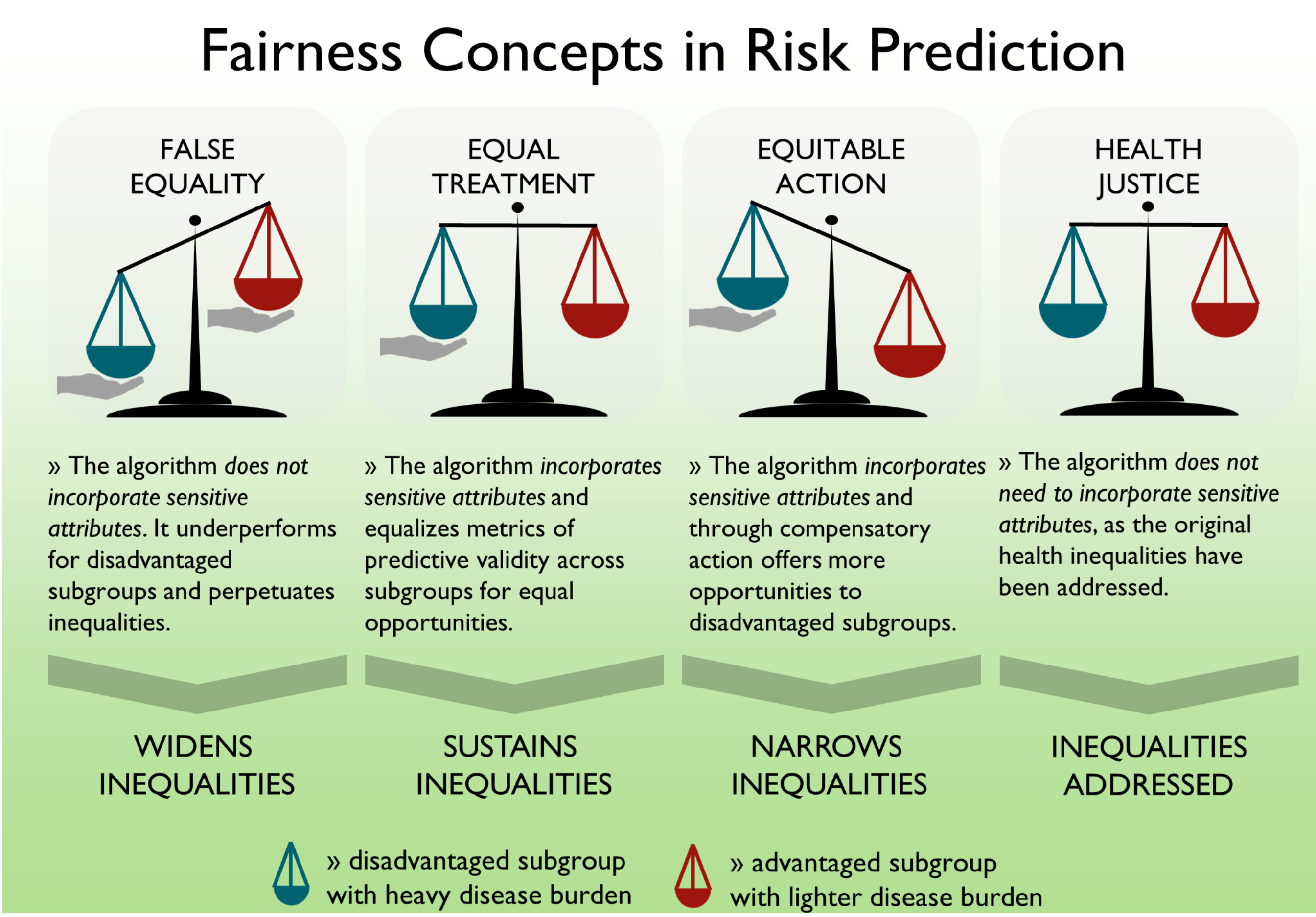

Figure 1 The figure depicts four concepts of fairness in algorithmic risk prediction. The scales represent the distribution of disease burden, with the disadvantaged subgroup represented in blue and the advantaged subgroup represented in red. The four panels illustrate how prognostic models may contribute to health justice.

individuals residing in the Netherlands showed that when the population was categorised into quintiles based on socioeconomic status, those in the lowest quintile experienced the most pronounced degree of underestimation of CVD risk.[15] Similarly, ethnic minorities (e.g., Surinamese) within the same population exhibited a greater degree of underestimation compared with individuals who self-reported their ethnicity as Dutch.[15] These forms of algorithmic unfairness will result in harm to marginalised groups and a loss of healthcare productivity.[16 17] Therefore, it is essential to explicitly consider socioeconomic determinants of CVDs in the development and validation of risk prediction models to ensure that they offer equitable and fair predictions to all population subgroups. A comprehensive systematic review from 2016 that identified 363 different CVD prediction models showed that only ~3% of the models included socioeconomic determinants as predictors.[18] Notably, even in the case of more commonly employed models, such as the QRISK,[19] JBS3[20] and ASSIGN[21] models (all developed in the UK), which do incorporate data on socioeconomic determinants, this is typically achieved by the inclusion of area-level or neighbourhood-level deprivation scores. The problem with this approach is that it offers a lower level of granularity compared with the hypothetical incorporation of individual-level information on socioeconomic determinants. Also, reliance on area-level or neighbourhood-level data on socioeconomic status may raise concerns related to the ecological fallacy and may overlook critical individual-level variation within areas. Indeed, despite the incorporation of area-level deprivation in the QRISK model, it did not demonstrate a clear superiority over the Framingham score (lacking socioeconomic determinants) in predicting CVD events within a triethnic cohort from the UK.[22] The SCORE2 algorithm, tailored for four risk regions within the EU and widely adopted in national healthcare systems in the EU, lacks even basic area-level socioeconomic determinants. Consequently, it offers a limited and potentially misleading perspective on equality and it may, in fact, reinforce and broaden existing disparities.

Transforming CVD prediction to promote health equality

Algorithmic fairness is a rapidly evolving field that aims to provide equitable predictions across population subgroups defined by sensitive attributes.[23] Predictive algorithms are often developed to provide the most accurate predictions, with less emphasis on fairness principles. This can result in unequal rates of false positives and false negatives across population subgroups due to overestimation and underestimation of individual risk. To address this issue, a number of (often mutually exclusive) metrics have been developed to audit existing algorithms, such as *equalised odds* and *predicted rate parity*, which compare different metrics of predictive validity derived from the confusion matrix after a classification process.[24] By convention, an algorithm can be considered fair when the predictive validity metrics are similar to each other to a prespecified degree in the examined subgroups. These metrics can also be used in the development phase of a novel algorithm by placing constraints on model development, forcing the resulting model to be simultaneously accurate and fair according to the chosen metrics. One possible outcome of a fair prognostic algorithm would be equalised rates of false positives and false negatives across population subgroups according to socioeconomic status. This would ensure that groups with low and high socioeconomic status have equal opportunities and distribution of healthcare resources (on average), satisfying the definition of health equality (figure 1). Another approach would be to focus on precision medicine initiatives to identify predictors of CVDs specific to marginalised population subgroups, providing more accurate predictions in these specific groups. This would require more research resources to be allocated to the study of these populations and would ideally result in updated, superior, subgroup-specific models being provided to healthcare professionals. In the USA, subgroup-specific CVD prediction models, like the sex-specific Reynolds risk scores, have been successfully developed.[25 26] These models have distinct sets of predictors tailored to optimise predictive performance for each subgroup.

Either way, explicitly incorporating socioeconomic determinants in CVD models is crucial and represents a clear step towards health equality. Incorporating socioeconomic determinants in the model development is also likely to improve model performance in general, as a recent systematic review has noted.[27] In summary, implementing algorithmic fairness in prognostic models is imperative for achieving health equality.

Positive discrimination in CVD prediction as a vehicle for health equity?

Equality and equity are two separate concepts. Equality refers to equal distribution of resources, while equity represents a fairness concept where resources are allocated according to need, in a non-uniform fashion.[28] One might argue that removing disparities or closing health gaps is theoretically and practically impossible through providing equal care to disparate subgroups, as this approach would likely only *sustain* the current health gaps, rather than addressing them. In this setting, one might define equity as providing additional resources and promoting the marginalised, underrepresented or otherwise in need, often referred to as 'affirmative action' in the USA, and 'positive discrimination' in the EU. To underscore the potential of positive discrimination strategies, it needs to be acknowledged that focusing solely on socioeconomic factors might miss important contributors to CVD, such as systemic racism, access and utilisation to healthcare, and healthcare literacy. These complex features, though correlated with measurable attributes such as race, ethnicity and basic socioeconomic features, present challenges for inclusion in predictive models, necessitating alternative strategies—such as positive discrimination—to improve care for marginalised populations and narrow health disparities. However, positive discrimination, given finite resources, would necessitate the redistribution of healthcare resources towards those in need and subtracting from those who currently benefit the most from the system, presenting an ethical dilemma. In terms of prognostic risk prediction models, such as SCORE2, an equitable approach would be to redesign the model so that proportionally, more individuals from vulnerable subgroups are prioritised for preventive intervention. This could be achieved, for instance, by lowering the risk score threshold for those with lower socioeconomic status (figure 1). This approach is not unprecedented. In the USA, for instance, a simple scoring system known as the Prediabetes Risk Test[29] is used for pre-diabetes and diabetes screening. Notably, this system acknowledges that certain ethnic and racial minority groups are at higher risk for these conditions, encouraging all individuals from these groups to consult their doctors *regardless* of their scores. This approach represents a form of positive discrimination aimed at addressing health disparities, going beyond simple score adjustments to ensure equitable access to healthcare resources. While this approach may be controversial, there are arguments in favour of it when the preventive intervention is non-invasive, such as prescribed physical activity, lifestyle counselling, dietary targets or just closer and more frequent monitoring. The main argument against implementing this approach is the inevitable overdiagnosis (increase in false positives) among the disparate subgroup, which carries risks related to stigma, anxiety and additional financial or time constraints, representing an additional burden to marginalised communities and healthcares.[30 31] However, this compensatory action might also serve as a conduit to 'tip the balance' and equalise rates of CVD incidence across population subgroups over a period of time.

The question of whether prognostic risk prediction models can promote health equity remains to be answered through experimental research (e.g., the testing of whether predictive models improve patient outcomes in randomised clinical trials), potential clinical implementation and subsequent epidemiological analysis. It is also important to examine the ethical and legal ramifications of using positive discrimination in healthcare, including the thorough investigation of potential harms and benefits to ensure that any developed models are consistent with the principles of fairness and comply with current legislation.

CONCLUSIONS

To ensure that prognostic models promote health equity, it is essential to explicitly consider sensitive attributes such as socioeconomic determinants on the individual level in the development and validation of these models. Without these considerations, medical decision-makers will be left to rely on their medical domain knowledge and intuition to address health gaps, which can lead to additional biases in the healthcare process. Additionally, algorithms should be developed and validated using data from diverse populations, and investigators should report subgroup-specific metrics of predictive validity. Special attention should be given to the identification, exploration and proper discussion of societal and data biases before model development. Neglecting to consider societal and data biases can lead to biased algorithms. For instance, differential rates of healthcare utilization have been mistakenly employed as indicators of health status, leading to the development of an algorithm that automates the enrollment of patients into preventive interventions.[32] Other aspects, such as differential rates of missing data, and differential misclassification can similarly bias findings, and should be appropriately explored. This is now more important than ever, as artificial intelligence algorithms might obscure and perpetuate these data biases. For these reasons, it is crucial that any algorithms are explainable and interpretable to all stakeholders so that potential biases can be identified and addressed. The implementation of critical checkpoints and continuous monitoring of clinically implemented algorithms will also assist in determining which algorithms are performing fairly, and if not, what changes can be made to improve them.

It is important to note that the implementation of algorithmic fairness in prognostic models is not a complete solution, but rather a possible entry point to promoting health equality. Addressing the root causes of inequalities, such as systemic racism, discrimination and marginalisation, as well as the inequalities themselves, such as disparities in income, education, healthcare literacy, living and working conditions, and access to quality healthcare, will allow populations to safely use scores such as SCORE2 to provide equal care. This represents achieving health justice (figure 1), the ultimate definition of fairness, where even risk prediction algorithms that are not aware of sensitive attributes will provide equal healthcare opportunities to all.

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