A Bayesian Causal Inference Approach for Assessing Fairness in Clinical Decision-Making

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Abstract

Fairness in clinical decision-making is a critical element of health equity, but assessing fairness of clinical decisions from observational data is challenging. Recently, many fairness notions have been proposed to quantify fairness in decision-making, among which causality-based fairness notions have gained increasing attention due to its potential in adjusting for confounding and reasoning about bias. However, causal fairness notions remain under-explored in the context of clinical decision-making with large-scale healthcare data. In this work, we propose a Bayesian causal inference approach for assessing a causal fairness notion called principal fairness in clinical settings. We demonstrate our approach using both simulated data and electronic health records (EHR) data.

Keywords: health equity, causal fairness, causal inference, potential outcomes, clinical decision-making

1. Introduction

Assessing fairness in clinical decision-making is an important element of equitable health care. Decisions are made by clinicians on a daily basis that directly impact patient care, but how these decisions are made is a complex process. While the medical ideal is to base decisions on a patient's health condition, this is not the reality. Gender, race, ethnicity, socioeconomic status, and other sensitive attributes can influence clinicians' decision-making process, raising important concerns about inequity in health and health care (Dehon et al., 2017; FitzGerald and Hurst, 2017; Aberegg and Terry, 2004; van Ryn and Burke, 2000).

There are many perspectives on how to quantify fairness. A major distinction among the existing fairness criteria is the use of causal reasoning. Associational fairness notions, such as statistical parity (Dwork et al., 2012), calibration (Chouldechova, 2017), and accuracy, do not rely on causal reasoning and estimate fairness based on observed data alone. On the other hand, causal fairness notions, such as counterfactual fairness and path-specific causal fairness, rely on knowledge about the data generating process (e.g., a structural causal model) to assess fairness. Serious concerns have been raised about associational fairness because they ignore the confounding effect and as a result, multiple fairness notions can't be simultaneously satisfied on a given dataset (Rahmattalabi and Xiang, 2022; Makhlouf

et al., 2020; Loftus et al., 2018). Given the large number of existing fairness notions, what fairness metrics are appropriate for clinical settings remains a question.

In medicine, the idea of fairness is expressed as *health equity*. Health equity can be defined in multiple ways. According to *Communities in Action: Pathways to Health Equity* (National Academies of Sciences, Engineering, and Medicine, 2017), "*health equity is the state in which everyone has the opportunity to attain full health potential and no one is disadvantaged from achieving this potential because of social position or any other socially defined circumstance.*" Based on this definition of health equity, we explore the existing fairness notions to discover potential metrics for assessing fairness in health care.

The contribution of this work is as follows. First, we propose a novel Bayesian causal inference approach for estimating a causal fairness notion called *principal fairness*. Second, our simulation experiments comparing non-causal fairness notions to principal fairness suggest that principal fairness, which evaluates the fairness of decisions among patients with similar health potential, maybe a more appropriate fairness metric in the domain of healthcare. Third, we demonstrate the proposed approach in assessing the fairness of clinical decisions in a real medical dataset where we discover gender and racial disparities in assigning revascularization treatment for patients with coronary artery disease.

2. Problem Formulation

As a working example, assume the research question is whether a treatment for heart disease is assigned in a fair way between men and women. The sensitive attribute is the patient's gender, and the outcome of interest is whether the patient experiences a heart attack within one year post-treatment.

Principal fairness is introduced by Imai and Jiang (2021). It works in the potential outcomes framework of causal inference (Rubin, 1974; Imbens and Rubin, 2015). Denote the variables in the clinical decision-making process as follows. For the i-th patient, let $A_i \in \{0, 1\}$ be the sensitive attribute (e.g., gender), $D_i \in \{0, 1\}$ be a binary medical decision on a treatment, and $X_i \in R^M$ be an M-dimensional vector of observed pre-treatment covariates (e.g. diagnoses, medications, and lab measurements). Finally, let $Y_i \in \{0, 1\}$ be a binary health outcome (e.g., heart attack following treatment), where $Y_i = 1$ means the outcome occurs (e.g., the patient experiences a heart attack). Let $Y_i(d)$ be the potential value of the outcome when the decision is $D_i = d$. For a binary decision, there are two potential outcomes for each patient, $Y_i(0)$ and $Y_i(1)$. For example, $Y_i(0) = 1$ means the i-th patient would have a heart attack within one year if not treated with heart surgery, and $Y_i(1) = 0$ means that the same patient would not have a heart attack for at least one year if with surgery.

The data live in a joint distribution $p(D, A, \mathbf{X}, Y(0), Y(1))$ with half of the potential outcomes missing. The missingness is due to the fact that a patient can only be observed under one of the two possible treatments, surgery ($D_i = 1$) or no surgery ($D_i = 0$). Thus, only the potential outcome following the observed treatment is observed ($Y_i = Y_i(D_i)$). We introduce ways to estimate the missing potential outcome following Bayesian Causal inference. For now, assuming both potential outcomes are handed over to you.

We first define the health potential of a patient. A patient's health potential H_i is defined as the joint of all potential outcomes, $H_i = (Y_i(0), Y_i(1))$. For a binary treatment and a

binary outcome, there are four principal strata, $(Y_i(0), Y_i(1)) \in \{(0,0),(1,0),(0,1),(1,1)\}$, which we name stable, treatable, better-without, and severe respectively.

Principal fairness states that a decision satisfies principal fairness if the decision is independent of the sensitive attribute conditioning on the principal strata, $p(D_i \mid H_i, A_i) = p(D_i \mid H_i)$. In our example, this means that if men and women have an equal chance of being treated conditioning on they have the same health potential, then the decision is fair. This definition allows patients with different health potentials (stable vs severe) to have a different probability of being treated.

Based on the definition of principal fairness, the level of violation of principal fairness can be measured by comparing the decision probabilities between the two sensitive groups within a stratum, that is,

$$\Delta(h) = p(D_i = 1 \mid A_i = a, H_i = h) - p(D_i = 1 \mid A_i = a', H_i = h). \tag{1}$$

When $\Delta(h) = 0 \quad \forall h$, then principal fairness is satisfied across all strata. Otherwise, principal fairness is violated.

3. Methods

We develop a Bayesian causal inference method to estimate the principal fairness of a clinical decision. The observed data is $\mathcal{D} = \{D_i, A_i, \mathbf{X}_i, Y_i\}_{i=1}^n$. Because only one potential outcome is observed in the data, $Y_{obs,i} = Y_i(D_i)$, we need to estimate the missing potential outcome $Y_{mis,i} = Y_i(1 - D_i)$, before we can estimate principal fairness. The missingness of potential outcomes is known as the fundamental problem of causal inference (Holland, 1986). The potential outcomes are identifiable under standard causal inference assumptions.

Three assumptions are needed for the potential outcomes to be identifiable from observational data: ignorability, overlap, and consistency(Rubin, 1974).

1. Ignorability: $(Y(0), Y(1)) \perp\!\!\!\perp D \mid \mathbf{X}$
2. Overlap: $0 < p(D_i = 1 \mid \mathbf{X}_i = \mathbf{x}) < 1 \; \forall \mathbf{x}$
3. Consistency: $Y_i(D_i) = Y_i$

Ignorability states that there is no unobserved confounding. Under ignorability, the distribution of the potential outcomes are identifiable from the observed data, that is, $\mathbb{E}[Y_i(d)] = \mathbb{E}_X[\mathbb{E}_Y[Y_i \mid \mathbf{X}_i, D_i = d]]$. Overlap assumes that the treatment and the control have non-zero probabilities of being assigned to patients. Violation of overlap leads to poor estimation of the potential outcomes. Consistency assumes that the observed outcome is equal to the potential outcome corresponding to the observed treatment.

Under the three assumptions for causal identification, we can proceed with the causal estimation of potential outcomes. We follow the idea of Bayesian causal inference that treats the estimation problem as a missing data problem (Rubin et al., 2018). The main advantage of Bayesian causal inference is that it models the data distribution in a generative way using probability distributions, which inherently estimates the uncertainty of the causal effect of interest.

The posterior predictive distribution of Y_{mis} is $Pr(Y_{mis} \mid X, A, Y_{obs}, D)$. Applying the conditional probability formula, we have

$$Pr(Y_{mis} \mid X, A, Y_{obs}, D) = \frac{Pr(X, A, Y(0), Y(1))Pr(D|X, A, Y(0), Y(1))}{\int Pr(X, A, Y(0), Y(1))Pr(D|X, A, Y(0), Y(1))dY_{mis}} \quad (2)$$

Under ignorability,

$$\Pr(D|X, A, Y(0), Y(1)) = Pr(D|X, A).$$

Thus, Eq. 2 becomes

$$Pr(Y_{mis} \mid X, A, Y_{obs}, D) = \frac{Pr(X, A, Y(0), Y(1))}{\int Pr(X, A, Y(0), Y(1))dY_{mis}} \quad (3)$$

Eq. 3 reveals that under ignorability, all we need to model is $Pr(X, A, Y(0), Y(1))$, a distribution of only the pre-treatment variables reflecting characteristics of the patient, independent of the treatment.

We assume the distributions of $(X, A, Y(0), Y(1))$ for each individual i are independent and identically distributed (iid). Given some model parameter θ and prior distribution over the parameter $p(\theta)$,

$$Pr(X, A, Y(0), Y(1)) = \int \left[\prod_{i}^{N} f(X_i, A_i, Y_i(0), Y_i(1) \mid \theta) \right] p(\theta) d\theta. \quad (4)$$

We use the chain rule to factorize $f(X_i, A_i, Y_i(0), Y_i(1) \mid \theta)$ as follows:

$$f(X_i, A_i, Y_i(0), Y_i(1) \mid \theta) = f(Y_i(0), Y_i(1) \mid X_i, A_i, \theta_{y_0 y_1}) f(X_i, A_i \mid \theta_{xa}), \quad (5)$$

where $\theta_{y_0 y_1}$ is the parameter specifying the conditional distribution of $Y_i(0), Y_i(1)$ given X_i and A_i, and θ_{xa} is the parameter specifying the marginal distribution of X_i and A_i. Both $\theta_{y_0 y_1}$ and θ_{xa} are functions of θ. This factorization allows us to predict the missing potential outcomes Y_{mis} from the observed information (X, A and Y_{obs}).

Now we can apply the chain rule again to factorize $f(Y_i(0), Y_i(1) \mid X_i, A_i, \theta_{y_0 y_1})$ into two parts based on treatment assignment. Let $\mathcal{I}_1$ and $\mathcal{I}_0$ denote the set of indices in the treated and control group respectively. For the treated group ($i \in \mathcal{I}_1$), that is,

$$f(Y_i(0), Y_i(1) \mid X_i, A_i, \theta_{y_0 y_1}) = f(Y_i(0) \mid X_i, A_i, Y_i(1), \theta_{y_0 \mid y_1}) f(Y_i(1) \mid X_i, A_i, \theta_{y_1}). \quad (6)$$

For the control group ($i \in \mathcal{I}_0$), that is,

$$f(Y_i(0), Y_i(1) \mid X_i, A_i, \theta_{y_0 y_1}) = f(Y_i(1) \mid X_i, A_i, Y_i(0), \theta_{y_1 \mid y_0}) f(Y_i(0) \mid X_i, A_i, \theta_{y_0}). \quad (7)$$

In order to impute the missing potential outcomes, the following (conditional) independence relationships are usually assumed:

$$f(Y_i(0), Y_i(1) \mid X_i, A_i, \theta_{y_0 y_1}) = f(Y_i(0) \mid X_i, A_i, \theta_{y_0}) f(Y_i(1) \mid X_i, A_i, \theta_{y_1}) \tag{8}$$

and

$$p(\theta_{y_0 y_1}) = p(\theta_{y_0}) p(\theta_{y_1}). \tag{9}$$

Eq. 8 holds under the assumption that the two potential outcomes are conditionally independent given X_i, A_i and the parameter governing the conditional distribution. Eq. 9 holds under the assumption that the parameters governing these conditional distributions are independent a priori.

Based on Eq. 8 and Eq. 9, we can build probabilistic models to estimate the missing potential outcomes and compute the fairness metric.

The algorithm is summarized as follows.

Algorithm 1: Bayesian Principal Fairness Assessment Algorithm

Input: $\mathcal{D} = \{D_i, A_i, \mathbf{X}_i, Y_i\}_{i=1}^n$
Output: $\Delta(h)\ \forall h$
Estimate $q_\phi(\theta_{y_0})$ with VI
Estimate $q_\phi(\theta_{y_1})$ with VI
for $s \leftarrow 1$ **to** S **do**
  $\theta_{y_0} \sim q(\theta_{y_0})$
  $\theta_{y_1} \sim q(\theta_{y_1})$
  $\mathrm{Y}_i(0) \sim \mathrm{Bern}\Big(p(Y_i(0) \mid X_i, A_i, \theta_{y_0})\Big), i \in \mathcal{I}_1$
  $\mathrm{Y}_i(1) \sim \mathrm{Bern}\Big(p(Y_i(1) \mid X_i, A_i, \theta_{y_1})\Big), i \in \mathcal{I}_0$
  Assign $\mathrm{H}_i = (Y_i(0), Y_i(1))$
  Compute $\Delta(h)\ \forall h$
end

There are two parameters to be estimated: θ_{y_0}, the parameter for estimating the potential outcome under no treatment, and θ_{y_1}, the parameter for estimating the potential outcome under treatment. We fit Bayesian logistic regression models to estimate the parameters. We use mean-field variational inference (VI) to approximate the posterior distribution of the parameters (Jordan et al., 1999; Wainwright and Jordan, 2008; Blei et al., 2017). Variational inference turns the inference problem into an optimization problem. The inference procedure for θ_{y_0} and θ_{y_1} is essentially the same, so we use θ_{y_0} to illustrate. Set $q_\phi(\theta_{y_0})$ to be a variational family of approximate posterior distributions, indexed by variational parameters ϕ. Variational inference aims to find the setting of ϕ that minimizes the KL divergence between q_ϕ and the posterior. Minimizing this KL divergence is equivalent to maximizing the evidence lower bound (ELBO),

$$\mathbb{E}_{q_\phi}\left[\log p(\theta_{y_0}) + \log p(y \mid \theta_{y_0}) - \log q_\phi(\theta_{y_0})\right]$$

The ELBO sums the expectation of the log joint, which consists of three components – the log prior, the log-likelihood and the entropy of the variational distribution.

To approximate the posterior we set the variational family to be the mean-field family. The mean-field family factorizes over the latent variables, where j indexes covariates:

$$q_\phi(\theta_{y_0}) = \prod_j q_\phi(\theta^j_{y_0})$$

We posit a Gaussian distribution over the variational distribution,

$$q(\theta^j_{y_0}) = \mathcal{N}(\mu_j, \sigma^2_j)$$

Our goal is to optimize the ELBO with respect to $\phi = \{\mu, \sigma^2\}$.

To train the model, we perform stochastic gradient ascent using Adam (Kingma and Ba, 2017). We approximate gradients using the reparameterization trick (Rezende et al., 2014; Kingma and Ba, 2017).

Code is available in the Supplementary materials for review, and will be made open-source at https://github.com/bayesPF4Health.

4. Simulation

We simulate a dataset to show that the proposed algorithm can correctly assess whether a decision satisfies principal fairness, while associational fairness notions fail to do so. Simulation is necessary for evaluation because the ground truth for both potential outcomes are available in a simulation, and never available in any real datasets.

Setup We simulate the sensitive attribute (e.g. gender) as $A_i \sim \text{Bern}(0.5)$, and pre-treatment covariates as $\mathbf{X}_i \sim \mathcal{N}_m(0, 1)$, $m = 100$. Then we simulate the two potential outcomes as $Y_i(d) \sim \text{Bern}(\sigma(f(\mathbf{X}_i, d)))$, where $d \in \{0, 1\}$. Notice that the potential outcomes does not depend on A, which means that no group is inherently healthier or sicker than others given all measured covariates $\mathbf{X}$. This is an essential assumption in principal fairness (Imai and Jiang, 2021). The principal stratum for each individual H_i is assigned based on each individual's joint potential outcomes. Then, treatment is assigned as $D_i \sim \text{Bern}(p_{h,a})$, where $p_{h,a}$ is the decision probability for principal stratum h and sensitive attribute a. To make the treatment violate principal fairness, we simulate the treatment such that the probability of being treated is 20% higher for males than females in the stable stratum, and 20% lower for males than females in the severe stratum. Details about the simulation setup are in the Appendix.

Fairness metrics We compare findings from principal fairness against findings from three associational fairness metrics. We show that a decision that violates principal fairness can be fair, or unfair based on other fairness metrics. The associational fairness notions are as follows.

1. Statistical parity: $p(D_i \mid A_i) = p(D_i)$
2. Calibration: $p(Y_i \mid D_i, A_i) = p(Y_i \mid D_i)$
3. Accuracy: $p(D_i \mid Y_i, A_i) = p(D_i \mid Y_i)$

4.1. Results

The results of the simulation are shown in Figs. 1 and 2. First, the proposed algorithm is able to detect the unfair decision and estimate the level of unfairness $\Delta(h)$, which rely on the estimation of the principal strata (Fig. 2). The proposed algorithm correctly identified the two strata (stable and severe) where decisions were made unfairly. Specifically, it is estimated that women are about 20% less likely to receive the treatment than men in the stable group, and about 20% more likely to receive the treatment in the severe group.

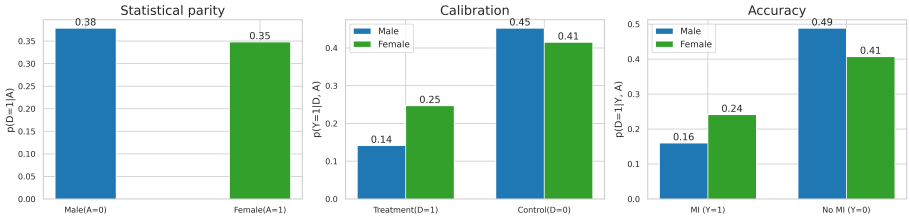


Figure 1: Associational fairness metrics from the simulation

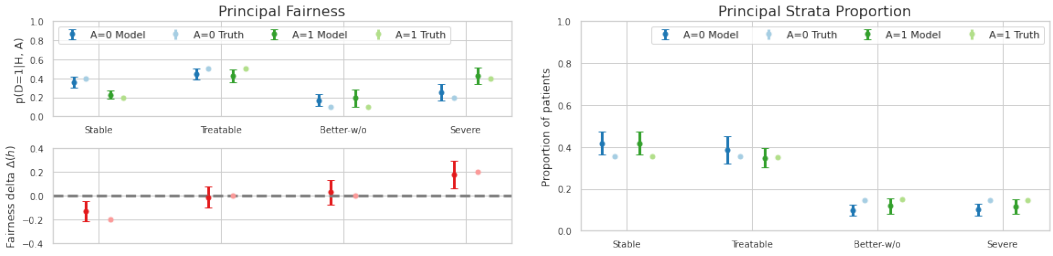


Figure 2: Fairness results from the simulation. Left: Principal fairness decision probabilities and level of violation metric $\Delta(h)$. Right: Proportion of principal strata. The proposed algorithm can detect unfair decisions and estimate levels of violation.

The results of the three associational fairness notions applied to the same dataset are shown in Fig. 1. Given the decision is unfair based on the simulation setup, statistical parity fails to detect the bias. Though this result is specific to this simulation, it is not hard to imagine other situations where this metric can fail to serve its purpose. For example, if more men than women admitted to the hospital are susceptible to heart attack, then a decision satisfying statistical parity can still be unfair because more men ought to be treated.

Calibration finds that the probability of having a heart attack is higher for women than men in the treatment group but lower in the control group. This metric has the same limitation as statistical parity that it fails to consider whether there is a difference in the underlying risk of heart attack between men and women. It also fails to account for the fact that which potential outcome is observed depends on the treatment assignment mechanism in the observational data. Furthermore, while the goal is to assess decision fairness, this metric focuses on outcome probability rather than decision probability, making it less intuitive to interpret.

Accuracy finds that the treatment is more likely to be received by women than men in the heart attack group, but the opposite is true in the no heart attack group. It is unclear whether the treatment is assigned more often to men or women given the conflicting messages from the two subgroups. Given that this metric also uses observed outcomes rather than potential outcomes for assessing fairness, above mentioned limitations also apply here.

The simulation confirms that the proposed algorithm is able to estimate principal fairness, and suggests that principal fairness is potentially a better metric than associational fairness metrics because it assesses fairness among patients with similar underlying health potential.

5. Empirical Study

We assess the fairness of clinical decisions on revascularization procedures in patients with coronary artery disease (CAD). Heart disease is the leading cause of death for men, women, and people of most racial and ethnic groups in the United States (Centers for Disease Control and Prevention, National Center for Health Statistics, 2022). Coronary heart disease is the most common type of heart disease, killing 382,820 people in 2020 in the United States–that's 1 in every 10 deaths (Centers for Disease Control and Prevention, National Center for Health Statistics, 2022; Tsao et al., 2022). Revascularization procedures, including percutaneous coronary intervention (PCI) and coronary artery bypass grafting (CABG), are common clinical procedures for treating CAD. Women, African Americans, and Hispanic populations have been found to have lower odds of receiving revascularization treatments and experience worse outcomes (Zea-Vera et al., 2022; Gusmano et al., 2019; Brown et al., 2008; Li et al., 2013). In this example, we apply the proposed algorithm along with other associational fairness metrics to assess the gender and racial fairness of revascularization treatments using EHR data.

5.1. Study Design

Database Data for this study come from an EHR database with over 6 million patient records collected in an academic medical center in a metropolitan area in the United States. The database is formatted according to Observational Health Data Sciences and Informatics (OHDSI) Observational Medical Outcomes Partnership Common Data Model (OMOP CDM) version 5 (Hripcsak et al., 2015).

Cohort definition The coronary artery disease (CAD) cohort consists of two groups, the treatment group and the control group. The treatment group is defined as patients treated with either PCI or CABG. The inclusion criteria include patients with no prior PCI or CABG treatment, and patients with at least one coronary arteriorsclerosis diagnosis within one year prior to treatment. The index date is the date of the treatment. For patients with multiple treatments in their records, only the earliest one is included. The control group consists of patients who meet the inclusion criteria but did not have either PCI or CABG. The index date for the control group is the earliest clinical visit with a coronary arteriorsclerosis diagnosis.

Feature extraction The primary outcome of interest is myocardial infarction (MI) within one year post index date. Pre-treatment patient features were extracted, including demo-

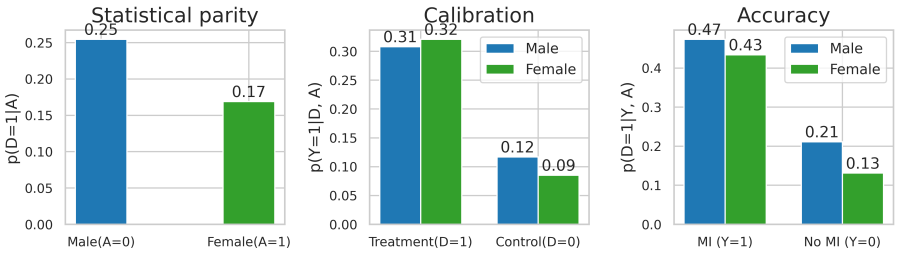


Figure 3: Associational Fairness (Gender) of decisions on revascularization.

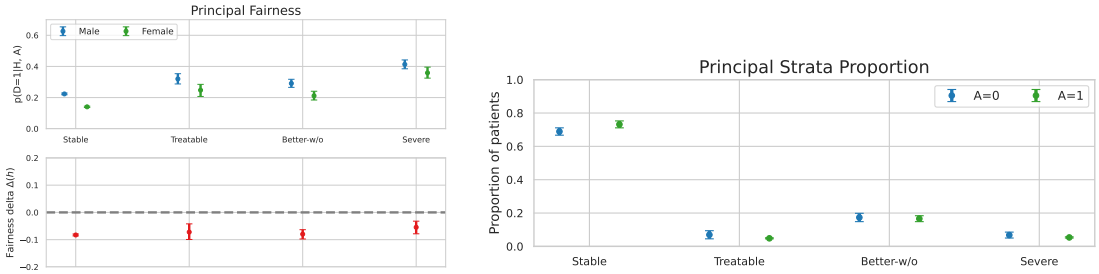


Figure 4: Gender fairness of decisions on revascularization. Left: (Gender) principal fairness. Right: Estimated proportion of principal strata in the cohort.

graphics (race, gender, age on index date), one-year diagnoses, and one-year medications. Patients with missing race or gender were excluded from the study. The final cohort consists of 64,279 patients, including 14,366 (22.3%) in the treatment group, and 429 features.

5.2. Results

Gender fairness Fig. 4 presents the fairness assessment with respect to gender. All four fairness metrics detect differences in the delivery of revascularization across gender, though the interpretations are different. Statistical parity indicates that male patients are more likely to receive treatment than female patients. Calibration indicates that the health outcome (heart attack) happens at a higher rate for male patients than for female patients in the one of the two treatment groups. Accuracy indicates male patients are more likely to receive the treatment than female patients in one of the two outcome groups. The differences shown by these metrics do not allow conclusions to be made regarding the fairness of treatment assignment, because whether there is any health difference at the baseline between men and women is not known. Principal fairness indicates that male patients are more likely to receive the treatment than female patients, even if they would benefit (or be harmed) equally from the treatment.

The principal strata proportion shows no distinctive difference between men and women (Fig. 4), or between Black and non-Black patients(Fig. 5). Most patients are in the stable stratum. This is surprising given the the time window for outcome to happen is one year.

Racial fairness All four fairness metrics find that Black patients are less likely to be treated with revascularization (statistical parity, accuracy, and principal fairness), and more likely to experience heart attack (calibration). The results are included in the Appendix. Fig. 5 presents the fairness assessment with respect to race.

6. Discussion

In this study, we develop a model to explore the potential of a causal fairness notion called principal fairness in assessing the fairness of treatment decisions.

Limitations There are several limitations to this approach. First, the proposed model for assessing principal fairness relies on assumptions for causal identification. For example, ignorability assumes *all* factors that contribute to the risk of the outcome are available. This is an untestable assumption and future work should explore the violation of ignorability on fairness estimation using sensitivity analysis.

Second, the proposed algorithm focuses on assessing treatment disparities, while health care is a dynamic process, factors that precede treatment decision-making, such as access to care, diagnosis disparities, and testing bias can potentially have an impact on the treatment decision. Future work should look into how to extend principal fairness to account for bias in other stages of care delivery using sequential models.

Last but not least, this work is subject to all limitations regarding the use of EHR for observational research (Hripcsak and Albers, 2013). In particular, the not-at-random missingness of race in half of the patient population in the EHR database can affect the fairness, validity, and generalizability of the method and the results.

Related Work Many metrics have been proposed for discrimination discovery. Statistical parity (Dwork et al., 2012), equality of opportunity, mistreatment parity, and predictive equality **?**Zafar et al. (2016); Corbett-Davies et al. (2017) are the most frequently reviewed associational metrics. Recently, a growing number of fairness notions are based on causality, reflecting the widely accepted idea that causal reasoning is essential for addressing the problem of fairness. By viewing discrimination as the presence of an unfair causal effect of the sensitive attribute on the decision, Qureshi et al. (2020) presents a method for causal discrimination discovery that adjusts for confounding using propensity score analysis. Some causal fairness takes a step further to distinguish direct and indirect discrimination based on path-specific effects. Zhang et al. (2019, 2016) leverage path-specific effects to discover and remove direct and indirect discrimination from observational data. Nabi and Shpitser (2018); Zhang and Bareinboim (2018a,b); Wang et al. (2019) developed various methods to quantify direct and indirect discrimination. Kilbertus et al. (2017) proposed discrimination criteria to qualitatively determine the existence of indirect discrimination. Huan et al. (2020) proposed to assess fairness by quantifying the difference in effort to achieve the same outcome. Kusner et al. (2017) introduced ab individual-level causal fairness criterion called counterfactual fairness, which states that a decision is fair toward an individual if it is the same as the decision that would have been taken in a counterfactual world where the sensitive attributes were different. Counterfactual fairness and principal fairness consider different variables as the intervention. Counterfactual fairness intervenes on the sensitive attribute directly, while principal fairness assesses fairness based on potential outcomes

under a different medical treatment, then uses this causal quantity to further assess fairness. It is intuitively more approachable to estimate the potential outcome with respect to medical treatment, than with respect to a sensitive attribute. Another difference is that principal fairness is population-level fairness, while counterfactual fairness is individual-level, but can be population-level with some modifications. The two levels of fairness do not imply each other (Imai and Jiang, 2021).

Fairness in Healthcare Leveraging established fairness metrics commonly used in predictive models, Sun et al. (2022) proposed a set of best practices to assess the fairness of phenotype definitions and related algorithmic fairness metrics to commonly used epidemiological cohort description metrics. Pfohl et al. (2019) developed an augmented counterfactual fairness criteria that extend the group fairness criteria of equalized odds for clinical risk prediction. The importance of fair machine learning for healthcare is emphasized in several perspectives and commentaries along with proposed guidelines (Chen et al., 2021; Gichoya et al., 2021; Ghassemi et al., 2020), but the gap between machine learning, fairness, and healthcare is still huge and needs to be filled to advance health equity.

References

Scott K. Aberegg and Peter B. Terry. Medical decision-making and healthcare disparities: The physician's role. *The Journal of Laboratory and Clinical Medicine*, 144(1):11–17, July 2004.

David M Blei, Alp Kucukelbir, and Jon D McAuliffe. Variational inference: A review for statisticians. *Journal of the American Statistical Association*, 112(518):859—877, 2017.

C. Perry Brown, Levi Ross, Ivette Lopez, Angela Thornton, and Gebre-Egziabher Kiros. Disparities in the receipt of cardiac revascularization procedures between blacks and whites: An analysis of secular trends. *Ethnicity & Disease*, 18(2 Suppl 2):S2–112–7, 2008.

Centers for Disease Control and Prevention, National Center for Health Statistics. About Multiple Cause of Death, 1999–2020. *CDC WONDER Online Database website. Atlanta, GA: Centers for Disease Control and Prevention*, 2022.

Irene Y. Chen, Emma Pierson, Sherri Rose, Shalmali Joshi, Kadija Ferryman, and Marzyeh Ghassemi. Ethical Machine Learning in Healthcare. *Annual Review of Biomedical Data Science*, 4(1):123–144, 2021.

Alexandra Chouldechova. Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments. *Big Data*, 5(2):153–163, June 2017.

S. Corbett-Davies, E. Pierson, A. Feller, Sharad Goel, and Aziz Z Huq. Algorithmic decision making and the cost of fairness. *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2017.

Erin Dehon, Nicole Weiss, Jonathan Jones, Whitney Faulconer, Elizabeth Hinton, and Sarah Sterling. A Systematic Review of the Impact of Physician Implicit Racial Bias on Clinical Decision Making. *Academic Emergency Medicine*, 24(8):895–904, 2017.

Cynthia Dwork, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Richard Zemel. Fairness through awareness. In *Proceedings of the 3rd Innovations in Theoretical Computer Science Conference*, ITCS '12, pages 214–226. Association for Computing Machinery, January 2012.

Chloë FitzGerald and Samia Hurst. Implicit bias in healthcare professionals: A systematic review. *BMC Medical Ethics*, 18(1):19, March 2017.

Marzyeh Ghassemi, Tristan Naumann, Peter Schulam, Andrew L. Beam, Irene Y. Chen, and Rajesh Ranganath. A review of challenges and opportunities in machine learning for health. *AMIA Summits on Translational Science Proceedings*, 2020:191, 2020.

Judy Wawira Gichoya, Liam G. McCoy, Leo Anthony Celi, and Marzyeh Ghassemi. Equity in essence: A call for operationalising fairness in machine learning for healthcare. *BMJ Health & Care Informatics*, 28(1):e100289, April 2021.

Michael K. Gusmano, Daniel Weisz, Catherine Allende, and Victor G. Rodwin. Disparities in Access to Revascularization: Evidence from New York. *Health Equity*, 3(1):458–463, August 2019.

Paul W. Holland. Statistics and Causal Inference. *Journal of the American Statistical Association*, 81(396):945–960, 1986.

George Hripcsak and David J Albers. Next-generation phenotyping of electronic health records. *Journal of the American Medical Informatics Association : JAMIA*, 20(1):117–121, 2013.

George Hripcsak, Jon D Duke, Nigam H Shah, Christian G Reich, Vojtech Huser, Martijn J Schuemie, Marc A Suchard, Rae Woong Park, Ian Chi Kei Wong, Peter R Rijnbeek, Johan van der Lei, Nicole Pratt, G Niklas Norén, Yu-Chuan Li, Paul E Stang, David Madigan, and Patrick B Ryan. Observational health data sciences and informatics (OHDSI): Opportunities for observational researchers. *Studies in health technology and informatics*, 216:574–8, 2015.

Wen Huan, Yongkai Wu, Lu Zhang, and Xintao Wu. Fairness through Equality of Effort. In *Companion Proceedings of the Web Conference 2020*, pages 743–751. Association for Computing Machinery, April 2020.

Kosuke Imai and Zhichao Jiang. Principal Fairness for Human and Algorithmic Decision-Making. *arXiv:2005.10400 [cs, stat]*, January 2021.

Guido W. Imbens and Donald B. Rubin. *Causal Inference for Statistics, Social, and Biomedical Sciences: An Introduction.* Cambridge University Press, 2015.

Michael I. Jordan, Zoubin Ghahramani, Tommi S. Jaakkola, and Lawrence K. Saul. An Introduction to Variational Methods for Graphical Models. *Mach. Learn.*, 37(2):183—233, 1999.

Niki Kilbertus, Mateo Rojas Carulla, Giambattista Parascandolo, Moritz Hardt, Dominik Janzing, and Bernhard Schölkopf. Avoiding Discrimination through Causal Reasoning. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc., 2017.

Diederik P. Kingma and Jimmy Ba. Adam: A Method for Stochastic Optimization. *arXiv:1412.6980 [cs]*, January 2017.

Matt J. Kusner, Joshua R. Loftus, Chris Russell, and Ricardo Silva. Counterfactual fairness. 2017.

Suhui Li, Arnold Chen, and Katherine Mead. Racial Disparities in the Use of Cardiac Revascularization: Does Local Hospital Capacity Matter? *PLOS ONE*, 8(7):e69855, July 2013.

Joshua R. Loftus, Chris Russell, Matt J. Kusner, and Ricardo Silva. Causal Reasoning for Algorithmic Fairness. *arXiv:1805.05859 [cs]*, May 2018.

Karima Makhlouf, Sami Zhioua, and Catuscia Palamidessi. Survey on Causal-based Machine Learning Fairness Notions. October 2020.

Razieh Nabi and Ilya Shpitser. Fair Inference On Outcomes. *arXiv:1705.10378 [stat]*, January 2018.

National Academies of Sciences, Engineering, and Medicine. *Communities in Action: Pathways to Health Equity*. National Academies Press, 2017.

Stephen Pfohl, Ben Marafino, Adrien Coulet, Fatima Rodriguez, Latha Palaniappan, and Nigam H. Shah. Creating Fair Models of Atherosclerotic Cardiovascular Disease Risk. In *Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*, AIES '19, pages 271–278. Association for Computing Machinery, January 2019.

Bilal Qureshi, Faisal Kamiran, Asim Karim, Salvatore Ruggieri, and Dino Pedreschi. Causal inference for social discrimination reasoning. *Journal of Intelligent Information Systems*, 54(2):425–437, April 2020.

Aida Rahmattalabi and Alice Xiang. Promises and Challenges of Causality for Ethical Machine Learning. *arXiv:2201.10683 [cs]*, January 2022.

Danilo Jimenez Rezende, Shakir Mohamed, and Daan Wierstra. Stochastic backpropagation and variational inference in deep latent gaussian models. volume 2, 2014.

Donald Rubin, Xiaoqin Wang, Li Yin, and Elizabeth Zell. *Bayesian Causal Inference: Approaches to Estimating the Effect of Treating Hospital Type on Cancer Survival in Sweden Using Principal Stratification*, volume 1. Oxford University Press, August 2018.

Donald B Rubin. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5):688, 1974.

Tony Y. Sun, Shreyas Bhave, Jaan Altosaar, and Noémie Elhadad. Assessing Phenotype Definitions for Algorithmic Fairness. *arXiv:2203.05174 [cs, q-bio]*, March 2022.

Connie W. Tsao, Aaron W. Aday, Zaid I. Almarzooq, Alvaro Alonso, Andrea Z. Beaton, Marcio S. Bittencourt, Amelia K. Boehme, Alfred E. Buxton, April P. Carson, Yvonne Commodore-Mensah, Mitchell S.V. Elkind, Kelly R. Evenson, Chete Eze-Nliam, Jane F. Ferguson, Giuliano Generoso, Jennifer E. Ho, Rizwan Kalani, Sadiya S. Khan, Brett M. Kissela, Kristen L. Knutson, Deborah A. Levine, Tené T. Lewis, Junxiu Liu, Matthew Shane Loop, Jun Ma, Michael E. Mussolino, Sankar D. Navaneethan, Amanda Marma Perak, Remy Poudel, Mary Rezk-Hanna, Gregory A. Roth, Emily B. Schroeder, Svati H. Shah, Evan L. Thacker, Lisa B. VanWagner, Salim S. Virani, Jenifer H. Voecks, Nae-Yuh Wang, Kristine Yaffe, Seth S. Martin, and null null. Heart disease and stroke Statistics—2022 update: A report from the american heart association. *Circulation*, 145(8):e153–e639, 2022.

Michelle van Ryn and Jane Burke. The effect of patient race and socio-economic status on physicians' perceptions of patients. *Social Science & Medicine*, 50(6):813–828, March 2000.

M. Wainwright and M. Jordan. Graphical models, exponential families, and variational inference. *Foundations and Trends in Machine Learning*, 1(1–2):1–305, 2008.

Yixin Wang, Dhanya Sridhar, and David M. Blei. Equal Opportunity and Affirmative Action via Counterfactual Predictions. *arXiv:1905.10870 [cs, stat]*, May 2019.

M. B. Zafar, I. Valera, M. Gomez-Rodriguez, and K. Gummadi. Fairness beyond disparate treatment & disparate impact: Learning classification without disparate mistreatment. *Proceedings of the 26th International Conference on World Wide Web*, 2016.

Rodrigo Zea-Vera, Sainath Asokan, Rohan M. Shah, Christopher T. Ryan, Subhasis Chatterjee, Matthew J. Wall, Joseph S. Coselli, Todd K. Rosengart, Waleed T. Kayani, Hani Jneid, and Ravi K. Ghanta. Racial/ethnic differences persist in treatment choice and outcomes in isolated intervention for coronary artery disease. *The Journal of Thoracic and Cardiovascular Surgery*, February 2022.

Junzhe Zhang and Elias Bareinboim. Fairness in Decision-Making — The Causal Explanation Formula. *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1), April 2018a.

Junzhe Zhang and Elias Bareinboim. Equality of Opportunity in Classification: A Causal Approach. In *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018b.

Lu Zhang, Yongkai Wu, and Xintao Wu. A causal framework for discovering and removing direct and indirect discrimination. *arXiv:1611.07509 [cs]*, November 2016.

Lu Zhang, Yongkai Wu, and Xintao Wu. Causal Modeling-Based Discrimination Discovery and Removal: Criteria, Bounds, and Algorithms. *IEEE Transactions on Knowledge and Data Engineering*, 31(11):2035–2050, November 2019.

Appendix A. Simulation Details

We simulate a data set to demonstrate the effectiveness of the algorithm in assessing the fairness of decisions. The benefit of a simulated dataset is that we have access to the ground truth (i.e., both potential outcomes for all individuals), which is not available in a real clinical setting. We simulate the data as follows:

1. Simulate a binary sensitive attribute as $A \sim \text{Bern}_n(0.5)$.

2. Simulate covariates as $\mathbf{X} \sim \mathcal{N}_{n\times m}(0,1)$, where $n = 5,000$ is the number of patients and $m = 100$ is the number of covariates.

3. Simulate potential outcomes as

$$Y_i(0) \sim \text{Bern}(\text{sigmoid}(\mathbf{x}_i^\top \theta_{y_0} + \theta_d 0))$$
$$Y_i(1) \sim \text{Bern}(\text{sigmoid}(\mathbf{x}_i^\top \theta_{y_1} + \theta_d 1))$$

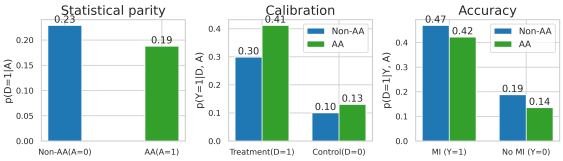
   where $\theta_{y_0}, \theta_{y_1} \sim \mathcal{N}_m(0,1)$. The effect size of the treatment $\theta_d = -1$.

4. Assign patients to principal strata.

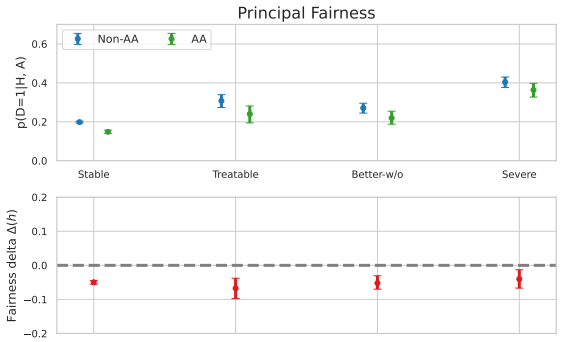
$$H_i = \begin{cases} 0(\text{stable}), & \text{if } Y_i(0), Y_i(1) = 0,0 \\ 1(\text{treatable}), & \text{if } Y_i(0), Y_i(1) = 1,0 \\ 2(\text{better-wo}), & \text{if } Y_i(0), Y_i(1) = 0,1 \\ 3(\text{severe}), & \text{if } Y_i(0), Y_i(1) = 1,1. \end{cases}$$

5. Simulate decision D_i conditioning on principal strata and the sensitive attribute as $D_i \mid H_i, A_i \sim \text{Bern}(p_{h,a})$ where $\Delta(h) = p_{h,a} - p_{h,a'} = 0$ for $h = 1,2$, and $\Delta(h) = p_{h,1} - p_{h,0} = -0.2$ for $h = 0$ and $\Delta(h) = p_{h,1} - p_{h,0} = 0.2$ for $h = 3$. That is, the decision is unfair in two of the four principal strata, and specifically, the decision favors individuals with $A = 0$ in the stable stratum but favors individuals with $A = 1$ in the severe stratum.

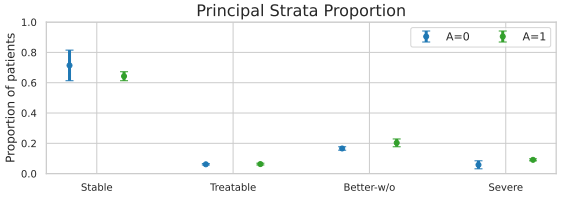
Appendix B. Racial Fairness in CAD



(*a*) Associational Fairness (Race)



(*b*) Principal Fairness (Race)



(*c*) Principal Strata Proportion (Race)

Figure 5: Racial fairness of decisions on revascularization. (a) The estimated proportion of principal strata in the cohort. (b) Fairness assessment based on four fairness metrics.