Impact of More Detailed Measures of Disease Severity on Racial Disparities in Cardiac Surgery Mortality among Native Hawaiians and Pacific Islanders

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Abstract

Studies that examine racial disparities in health outcomes often include analyses that account or adjust for baseline differences in co-morbid conditions. Often, these conditions are defined as dichotomous (Yes/No) variables, and few analyses include clinical and/or laboratory data that could allow for more nuanced estimates of disease severity. However, disease severity – not just prevalence – can differ substantially by race and is an underappreciated mechanism for health disparities. Thus, relying on dichotomous disease indicators may not fully describe health disparities. This study explores the effect of substituting continuous clinical and/or laboratory data for dichotomous disease indicators on racial disparities, using data from the Queen's Medical Center's (QMC) cardiac surgery database (a subset of the national Society of Thoracic Surgeon's cardiothoracic surgery database) as an example case. Two logistic regression models predicting in-hospital mortality were constructed: (I) a baseline model including race and dichotomous (Yes/No) indicators of disease (diabetes, heart failure, liver disease, kidney disease), and (II) a more detailed model with continuous laboratory values in place of the dichotomous indicators (eg, including Hemoglobin A1c level rather than just diabetes yes/no). When only dichotomous disease indicators were used in the model, Native Hawaiian and other Pacific Islander (NHPI) race was significantly associated with in-hospital mortality (OR: 1.57[1.29,2.47], P=.04). Yet when the more specific laboratory values were included, NHPI race was no longer associated with in-hospital mortality (OR: 1.67[0.92,2.28], P=.28). Thus, researchers should be thoughtful in their choice of independent variables and understand the potential impact of how clinical measures are operationalized in their research.

Keywords

Dichotomous Indicators, Risk Modeling, Prediction, Disparities, Statistical Methods

Abbreviations

ANOVA = analysis of variance
BMI = body mass index
HbA1c = hemoglobin A1c
LVEF = left ventricular ejection fraction
NHPI = Native Hawaiian and Pacific Islander
OR = odds ratio
QMC = Queen's Medical Center
STS = Society of Thoracic Surgeons

Introduction

Nearly 40 years since the US Department of Health and Human Services' landmark report highlighting racial and ethnic health disparities,[1] Native Hawaiian and other Pacific Islanders (NHPI) continue to bear a disproportionate burden of disease and adverse health outcomes. Compared with the rest of Hawai'i's population, NHPI have higher rates of chronic diseases, including heart disease, stroke, cancer, diabetes, and obesity, as well as longer hospital stays, poorer quality of life, and shorter life expectancy.[2]

Disease severity is a recognized, but underappreciated factor in health disparities. While NHPI have more chronic disease, several studies have noted that NHPI also have more severe disease.[3-6] Yet studies on disparities often consider comorbidities as dichotomous variables.[7-10] For instance, patients are usually categorized as either having diabetes or not. Even when more specific factors such as hemoglobin A1c (HbA1c) levels are available, they are dichotomized into 2 groups (eg, >6.5% or <6.5%) for ease of comparison. This operationalization of comorbid conditions is common in administrative datasets, allows for results that are more easily translated to clinical practice, and lends itself to simpler statistical analysis. However, this practice comes at the cost of loss of detail and potentially reduces the accuracy and precision of findings.

As an example, consider the following 2 patients: (1) A 46-year-old man with body mass index (BMI) of 30 and HbA1c of 6.6%, and (2) a 36-year-old man with BMI of 45 and HbA1c of 12.4%. Clinically, these patients likely have significantly different care needs and risk for a variety of complications. In fact, the first patient may be more similar to a non-obese, non-diabetic patient than to the second patient. However, dichotomous classification would group these 2 patients together and draw inferences from their combined data.

While previous studies have described the additional power gained by using continuous rather than dichotomous variables, this concept has not been consistently applied in research on health disparities. Many studies on health disparities utilize multivariable regression analyses in their work. This allows researchers to observe disparities on a population level and then use multivariable regression models to control for or explore potential mechanisms by adding risk factors, socioeconomic measures, and other variables as model coefficients. If race is still significant in the model after potential confounders and risk factors are included, researchers understand that there are lingering pathways through which disparities influence the outcome in question.[11,12] Underpowered or underspecified models thus hinder the ability to explore these issues, and it may be important to include more than just dichotomous disease indicators.

The purpose of this study is to better understand the extent to which racial/ethnic disparities are related to disease severity. The team uses the Queen's Medical Center's (QMC) cardiac surgery database as an example case, illustrating the difference in in-hospital mortality when different markers of disease are used and then considering the effects – if any – that these results have on the conclusions.

Methods

Study Design

The study is a secondary analysis of data collected for clinical and research purposes. It aims to serve as an illustrative example, rather than a precise description of in-hospital mortality following cardiac surgery. Discussions on the clinical applications of these data can be found elsewhere.[6,13]

Database

Data are from the cardiac surgery registry at QMC, which is a tertiary care, 500-bed, university-affiliated hospital in Honolulu, Hawai'i. This registry contains data on all cardiac surgeries performed from 2009 to 2020. Data were collected by trained nurse abstractors who performed detailed reviews of the medical record and assembled prospective patient-level data for each case using standard definitions and protocols outlined by the Society of Thoracic Surgeons (STS).[13]

Data on all cardiac surgeries performed from 2009-2020 in adults ≥18 years old were include in this study. Cases that were missing data on race were excluded, and the study population was limited to patients who were identified in our data as Asian, White, or NHPI (97.8% of the surgical population).

Sample

A total of 5097 cardiothoracic surgeries were conducted between 2009 and 2020. Fourteen surgeries were missing data on race or were among patients not classified as Asian, White, or NHPI, and an additional 32 were missing at least 1 disease indicator variable. Thus, the study population included 5051 surgeries in 5011 patients.

Less than 1% of records were missing laboratory values such as HbA1c, Left Ventricular Ejection Fraction (LVEF) and serum creatinine, and 1.5% were missing serum albumin. Given this small number, missing lab values were imputed using multiple imputations with the available data serving as predictors.

Dependent Variable

In-hospital mortality was extracted from the medical chart at the time of data entry into the registry, as per standard STS protocols. It is defined as death prior to discharge, however long the hospital stay.

Independent Variables

Independent variables included 5 common co-morbid conditions that are highly related to related to cardiovascular mortality: diabetes, heart failure, liver disease, kidney disease, and obesity. Each condition was included in the cardiac database as a "Yes/No" variable, except for diabetes, which had 5 categories based on treatment type. Diabetes was transformed into a "Yes/No" variable by defining the presence of diabetes to include patients treated with diet and/or medical therapy. Age and sex were included as additional covariates.

Severity was operationalized using laboratory values for HbA1c for diabetes, serum albumin for liver disease, and serum creatinine for renal disease. LVEF was used for heart failure and BMI for obesity.

Analytic Strategy

Chi-square analyses were used to identify differences in categorical variables between NHPI, Asian and White patients with follow up 2-by-2 analysis with White patients as reference if the 3-way results were significant. Continuous variables were analyzed with 3-way Analysis of Variance (ANOVA) with follow up Welch T-tests with White patients as reference if results were significant.

Two multivariable logistic regression models[14] predicting in-hospital mortality were constructed: (I) a baseline model including race, age, sex and dichotomous (Yes/No) indicators for the 5 co-morbid conditions (diabetes, heart failure, liver disease, kidney disease and obesity), and (II) a more detailed model with continuous laboratory values for diabetes (HbA1C), liver disease (albumin) and renal disease (creatinine), and measures of heart failure (LVEF) and obesity (BMI) in place of the dichotomous indicators. In both models, the primary measure of interest was the significance of the coefficient for NHPI race, with White race as a reference group. Sensitivity analyses were conducted to compare the results of models using the imputed data with models that used only patients with complete data. If there were no significant differences and unless otherwise specified, all results presented are from models built on imputed data.[15]

All analysis was conducted using R statistical software, version 4.0.5 (R Core team, Vienna, Austria). Results were considered statistically significant if the *P*-value was less than an $\alpha = .05$. Unless otherwise specified, model coefficients are presented as odds ratios [95% confidence intervals]. This study was approved the QMC Institutional Review Board.

Results

The distribution of races in the study population is similar to the distribution of races in the state's general population,[16] with 50.1% Asians, 25.1% NHPI, 22.6% White. NHPI were significantly younger (mean age: 60.0 years for NHPI vs 65.9 for Asian and 65.8 for White patients) and more likely to be female (31.3% for NHPI vs 26.8% for Asian and 21.6% for White patients). They were also significantly more likely to receive coronary artery bypass surgeries (76.3%) and aortic valve replacements than White patients (67.4%, **Table 1**).

NHPIs had a higher prevalence than Whites of diabetes (61.5% vs 32.4%), heart failure (37.1% vs 26.4%), kidney disease (9.96% vs 0.94%) and obesity (58.6% vs 34.7%). These prevalences also were significantly greater than Asian patients (**Table 2**). Compared with White patients, NHPIs had more severe diabetes (HbA1C: 7.2% vs 6.6%, $P<.001$), heart failure (LVEF: 50% vs 52%, $P=.027$), liver disease (albumin: 3.9 mg/dL vs 4.1 mg/dL, $P<.001$), kidney disease (creatinine: 1.8 mg/dL vs 1.5 mg/dL, $P=.028$), and obesity (BMI: 31.6 vs 27.3, $P<.001$).

There were no differences in unadjusted in-hospital mortality by race (White: 2.31%, Asian: 2.40%, NHPI: 2.20%). When only dichotomous disease indicators were used in the model, NHPI race was significantly associated with an increased in-hospital mortality (OR: 1.57 [1.29, 2.47], $P=.04$) (**Table 3**). Ultimately, this trend disappeared when more specific continuous lab values were included, with NHPI race was no longer associated with in-hospital mortality (OR: 1.67 [0.92, 2.28], $P=.28$).

Discussion

Studies that examine racial/ethnic disparities in health outcomes often rely on administrative data, which usually operationalize co-morbid conditions as dichotomous (yes/no) variables. These findings suggest that analyses that include more detailed measures of severity may produce different results than more generalized ones. In this study, NHPI who underwent cardiac surgery had significantly higher odds of in-hospital mortality when compared to White patients when dichotomous indicators of co-morbid conditions were used, but had similar odds of mortality when severity of co-morbid conditions was considered.

The value of augmenting administrative data with a parsimonious set of clinical laboratory data to enhance predictions of in-hospital mortality has been reported.[7,8] For example, Hanchate and colleagues found that adding laboratory data and vital signs to administrative data from the Veterans Health Administration, significantly improved hospital performance profiles on 30-day mortality, although it had limited effect on 30-day readmission and other hospital quality measures.[8] Similarly, an earlier study reported that augmenting statewide hospital administrative discharge data significantly improved the model prediction for inpatient mortality.[7] The current study extends these findings by demonstrating the impact of additional clinical data on estimates of racial/ethnic health disparities in Hawai'i.

On its face value, the results make sense. While NHPI carry a greater burden of cardiovascular refactors, they also typically present with more advanced disease, including more severe diabetes,[3,4] obesity, and renal insuffiency.[5] These findings suggest that disparities in NHPI in-hospital mortality following cardiac surgery may be partly explained by the severity of co-morbid conditions rather than their presence as a diagnosis per se.

This work has 2 major implications. First, studies that examine NHPI health disparities may need to consider the implications of using co-morbidity diagnoses vs. measures of co-morbidity severity as potential confounders in regression models. Second, while measures of co-morbidity severity may better account for racial/ethnic health disparities – indeed, NHPI and Whites had similar in-hospital mortality once co-morbidity severity was examined– this does not imply that racial/ethnic disparities no longer exist. Indeed, the National Institute of Minority Health and Health Disparities health disparities framework nicely connects domains and levels of influence to factors that may influence racial/ethnic differences in health-related behaviors and risk factors for disease.[17]

This study is subject to several limitations. First, it was limited to patients who underwent cardiac surgery at a single hospital in Hawai'i, and the results may not be generalizable to other institutions or to other health conditions. Second, the analytic approach assumed that the laboratory and clinical values were independent, linear, and normally distributed, which may not be valid. The authors chose this approach given the size of the study population and to aid in the interpretability of the study findings. Finally, the measures of co-morbidity severity may not have been ideal. Other measure of liver function (eg, aspartate transaminase, alanine transaminase), diabetes severity (eg, insulin resistance), renal function (eg, glomerular filtration rate), and heart failure (eg, left ventricular strain) were not available.

In conclusion, greater disease detail obtained using laboratory values can affect results when exploring racial disparities. While further research should expand these findings to other clinical scenarios and with better specified modeling, researchers should be cognizant of disease severity as a means through which disparities can affect health outcomes.

Table 1. Population Demographics of Cardiac Surgery Patients at the Queens Medical Center, 2009-2020					
	Total	**Asian**	**Native Hawaiian or Pacific Islander**	**White**	**P-value**
Total (n [%])	5051	2526 [50.1]	1268 [25.1]	1257 [22.6]	
Age (years + SD)	64.4 ± 11.3	65.9 ± 11.3	60.0 ± 11.0	65.8 ± 10.3	<.001
Female (%)	26.9	26.8	31.3	21.6	<.001
Mortality (%)	3.0	3.1	3.3	2.6	<.001
Procedure					
Coronary Artery Bypass Graft (%)	72.6	73.9	76.3	67.4	<.001
Aortic Valve Replacement (%)	11.7	10.6	8.6	16.7	<.001
Other (%)	15.7	15.5	15.1	15.9	.141

SD=standard deviation. *P*-values were calculated using Welch t-tests for age, chi-squared for female sex, and Fisher Exact tests for mortality.

Table 2. Comorbid Disease Prevalence and Severity by Race among QMC Cardiac Surgery Patients, 2009-2020			
	White	**Asian**	**NHPI**
Diabetes			
Yes, %	32.4	**53.3**	**61.5**
P-value		*P*=<.001	*P*=<.001
Hemoglobin A1c, mean ± SD	6.31 ± 1.56	**6.74 ± 1.49**	**7.20 ± 1.86**
P-value		*P*=<.001	*P*=<.001
Heart Failure			
Yes, %	26.4	26.8	**37.1**
P-value		*P*=.61	*P*=<.001
LVEF, mean ± SD	51.5 ± 12.4	52.8 ± 12.5	**50.5 ± 12.0**
P-value		*P*=.072	*P*=.027
Liver Disease			
Yes, %	5.21	**3.82**	**3.69**
P-value		*P*=<.001	*P*=<.001
Albumin, mean ± SD	4.12 ± 0.33	4.10 ± 0.52	**3.93 ± 0.50**
P-value		*P*=.68	*P*<.001
Renal Insufficiency			
Yes, %	0.94	**8.03**	**9.96**
P-value		*P*<.001	*P*<.001
Creatinine, mean ± SD	1.06 ± 0.84	1.64 ± 2.11	1.81 ± 2.29
P-value		*P*<.001	*P*=.028
Obesity			
Yes, %	34.7	**22.6**	**58.6**
P-value		*P*<.001	*P*<.001
Body Mass Index, mean ± SD	28.0 ± 5.67	27.0 ± 5.11	**31.6 ± 6.4**
P-value		*P*=.12	*P*<.001

LVEF = Left Ventricular Ejection Fraction; NHPI = Native Hawaiian and Pacific Islanders; QMC = Queens Medical center; SD = Standard Deviation. *P*-values were calculated using chi-squared tests for dichotomous indicators and t-tests for laboratory supplementation. In all cases, values for White patients were used as comparison groups. Bold text indicates a coefficient estimate that is significantly different than 0, at an alpha of .05.

Table 3. Comparison of In-Hospital Cardiac Surgery Mortality Logistic Regression Models Using Dichotomous Disease Indicators vs Supplementation with Laboratory Data

	Model Coefficient	
	Dichotomous Disease Indicators OR [95% CI], *P*-value	**Continuous Laboratory Indicators OR [95% CI], *P*-value**
Race		
NHPI	**1.57 [1.29, 2.47], *P*=.04**	1.67 [0.92, 2.28], *P*=.28
Asian	0.55 [0.16, 1.54], *P*=.30	0.24 [0.01, 1.36], *P*=.19
White	1	1
Diabetes		
Diabetes	1.84 [0.60, 0.5.16], *P*=.26	
A1c		1.18 [0.91, 1.03], *P*=.17
Heart Failure		
Heart Failure	1.91 [0.91, 3.97], *P*=.08	
LVEF		0.99 [0.95, 1.03], *P*=.62
Liver Disease		
Liver Disease	0.98 [0.96, 1.02], *P*=.17	
Albumin		**0.22 [0.09, 0.50], *P*=<.001**
Kidney Disease		
Kidney Disease	**4.12 [1.65, 9.63], *P*=.001**	
Creatinine		**1.19 [1.02, 1.36], P=.019**
Obesity		
Obesity	**.35 [0.11, 0.95], *P*=.048**	
BMI		**0.88 [0.77, 0.99], *P*=.037**

NHPI = Native Hawaiian and Pacific Islanders; A1c = Hemoglobin A1c; LVEF = Left Ventricular Ejection Fraction; BMI = Body Mass Index.
Model coefficients are displayed as Odds Ratio [95% Confidence Interval], with *P*-values in parentheses below based on a logistic regression model coefficients with significance determined by a Welch t-test. "No disease" is the reference group for the conditions. In the continuous laboratory models, the lab value or BMI was included in the model instead of the dichotomous disease indicator. Bold text indicates a coefficient estimate that is significantly different than 0, at an alpha of .05.

Conflict of Interest

None of the authors identify a conflict of interest.

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