Investigating Disparities, Clinical Variables, and Predictive Modeling in Organ Procurement

Benzon Carlitos Salazar

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Contents

Introduction

Organ transplantation is a critical component of modern healthcare, offering life-saving interventions for patients with end-stage organ failure. However, the process of organ procurement, where we have donor referral to successful retrieval, is influenced by a complex interplay of medical, logistical, and systemic factors. Despite ongoing efforts to improve equity and efficiency in organ donation, disparities persist across racial, socioeconomic, and geographic lines, raising concerns about fairness and resource allocation.

This project focuses on three interrelated themes in organ transplantation: disparities in organ procurement, clinical predictors of organ viability, and predictive modeling of procurement success. The analysis will draw on the **Organ Retrieval and Collection of Health Information for Donation (ORCHID) dataset**, a publicly available resource from PhysioNet comprising over **133,101 deceased donor referrals** across six **Organ Procurement Organizations (OPOs)** in the United States.

Specifically, the project will address the following questions:

1. **Disparities in Organ Procurement Outcomes** – To what extent do race, socioeconomic status, and geography influence procurement rates?

2. **Clinical Predictors of Procurement Success** – Which medical and laboratory parameters are most strongly associated with successful organ procurement?

3. **Predictive Modeling for Procurement Success** – Can statistical regression models be developed to accurately predict whether an organ will be successfully procured?

These questions are critical to improving the equity and efficiency of the organ transplantation system. By identifying disparities and enhancing predictive capabilities, this work aims to support more informed and equitable decision-making in organ allocation.

Data Collection Process

Methods and Tools

I will be relying on publicly available data from the **Organ Retrieval and Collection of Health Information for Donation (ORCHID) dataset**, hosted on **PhysioNet**. The data collection process will involve the following steps:

1. **Data Acquisition:**

- The dataset will be downloaded directly from PhysioNet using their web interface.
- If necessary, the PhysioNet API will be used for automated access.

2. **Data Structure and Organization:**

- The dataset consists of multiple CSV files, including **demographic, clinical, and procedural data** related to organ procurement.
- The tables will be linked using the unique **PatientID** field.

3. **Data Storage and Management:**

- The dataset will be stored in a **secure local repository** or **cloud storage** for easy access.
- R will be used for initial data exploration and preprocessing.

4. **Data Cleaning and Preprocessing:**

- Handling missing values by applying imputation or exclusion methods where appropriate.
- Standardizing variable formats for consistency in analysis.
- Filtering data based on relevant **study criteria**, such as time period, OPOs, or specific donor characteristics.

5. **Tools for Data Processing and Analysis:**

- **R (tidyverse, dplyr, ggplot2, caret, glmnet)** for data manipulation, visualization, and regression modeling.
- **R Markdown** for exploratory data analysis and documentation.

Data and Variables

The ORCHID dataset contains **demographic, clinical, and procedure information on deceased donor referrals**. Specifically, the dataset includes:

- **Demographic Data**: Race, age, sex, geographic region, socioeconomic proxies (hospital identifier, OPO region).
- **Clinical Variables**: Blood chemistry, hematology, arterial blood gas levels, infection status, cause of death, comorbidities.
- **Referral and Procurement Details**: Referral source, organ type, authorization status, OPO performance metrics.
- **Outcome Variable**: Whether the organ was successfully procured.

This dataset can be obtained from PhysioNet: https://physionet.org/content/orchid/2.0.0/

Questions and Concerns

Questions

1. What are the best statistical methods to adjust for confounding factors in organ procurement disparities?
2. How can missing data in clinical variables be handled to improve regression model accuracy?
3. What are the most effective regression techniques for predicting organ procurement success?

Concerns

- **Class Imbalance**: Procurement success may be significantly rarer than failures, which could affect model validity.
- **Data Bias**: Referral processes and OPO performance may introduce biases into the dataset.

Data Extraction and Clean up

All code chunks will not be evaluated since clean up was already performed prior to knitting this document.

The data cleanup involved reading raw CSV files from the ORCHID dataset, transforming them into a structured format, and saving the cleaned data as Parquet files. The key steps included:

1. **Reading Raw Data:**

   - CSV files for various event categories (e.g., ABG, CBC, Chemistry, Culture, Fluid Balance, Hemodynamics, etc.) were read into R.

2. **Data Cleaning and Transformation:**

   - Unnecessary columns (`RowID`, unnamed columns) were dropped.
   - Data was grouped by event type (e.g., `abg_name`, `cbc_name`, `chem_name`) and converted to a wide format using `pivot_wider()`.
   - Numeric values were coerced into appropriate data types (`double`).
   - An `opo_group` identifier was extracted from `PatientID` to categorize patients.
   - `tidyr::fill()` was used to propagate missing values up and down within each group.
   - Data was grouped by `PatientID`, `time_event`, and other relevant identifiers, then deduplicated using `slice_head()`.

3. **Data Output & Cleanup:**

   - The cleaned datasets were saved in Parquet format for efficient storage and processing.
   - Raw CSV files were removed after ensuring successful cleanup.
   - Memory was cleared using `rm(list = ls(all.names = TRUE))` and `gc()` to optimize performance.

This process ensured that data was well-structured, deduplicated, and efficiently stored while maintaining data integrity.

Below is an example of what the whole clean up process looked like.

```r
library(magrittr)

orchid_folder <- here::here("data-raw/physionet.org/files/orchid/2.0.0")
```

```r
abg_events <-
  readr::read_csv(here::here(orchid_folder, "ABGEvents.csv"))

abg_events_proc <-
  abg_events %>%
  dplyr::select(-c("...1", "RowID")) %>%
  dplyr::group_by(abg_name) %>%
  dplyr::mutate(row_id = dplyr::row_number()) %>%
  tidyr::pivot_wider(names_from = abg_name, values_from = value) %>%
  dplyr::ungroup() %>%
  dplyr::select(-row_id) %>%
  dplyr::mutate(opo_group = as.factor(substring(PatientID, 0, 4)),
                abg_ventilator_mode = as.character(abg_ventilator_mode),
                PH = as.double(PH),
                PCO2 = as.double(PCO2),
                PO2 = as.double(PO2),
                HCO3 = as.double(HCO3),
                BE = as.double(BE),
                O2SAT = as.double(O2SAT),
                FIO2 = as.double(FIO2),
                Rate = as.double(Rate),
```

```r
                 TV = as.double(TV),
                 PEEP = as.double(PEEP),
                 PIP = as.double(PIP))

abg_events_final <-
  abg_events_proc %>%
  dplyr::group_by(PatientID, time_event, abg_ventilator_mode, opo_group) %>%
  tidyr::fill(dplyr::everything(), .direction = "updown") %>%
  dplyr::slice_head() %>%
  dplyr::ungroup()

abg_events_final %>% nanoparquet::write_parquet(here::here("data", "abg_events.parquet"))
rm(abg_events, abg_events_proc, abg_events_final)
```

```r
# List of files to remove
files_to_remove <- c(
  "ABGEvents.csv",
  "calc_deaths.csv",
  "CBCEvents.csv",
  "ChemistryEvents.csv",
  "CultureEvents.csv",
  "FluidBalanceEvents.csv",
  "HemoEvents.csv",
  "referrals.csv",
  "SerologyEvents.csv"
)

# Remove files only if they exist
purrr::walk(files_to_remove, ~ {
  file_path <- here::here(orchid_folder, .x)
  if (file.exists(file_path)) {
    file.remove(file_path)
  }
})

rm(list = ls(all.names = TRUE)) # clear all objects including hidden objects
invisible(gc()) # free up memory
```

Purpose of Data Cleanup

The raw ORCHID dataset contains a wide variety of clinical event data stored across multiple CSV files. These files are structured in a long format with multiple redundant columns, inconsistent naming conventions, and varying data types. The primary objective of the cleanup was to create tidy, analysis-ready data by:

- Converting event-level long-form data into patient-level wide format.
- Ensuring consistency across numeric, categorical, and time-based variables.
- Removing duplicate rows, irrelevant columns, and noise.
- Storing processed outputs in a space-efficient, analysis-friendly format (`.parquet`).

This enables downstream applications such as predictive modeling, visualization, and exploratory data analysis to proceed without further data wrangling.

Overview of Files Processed

Raw File Name	Description	Output Filename
`ABGEvents.csv`	Arterial blood gas measurements	`abg_events.parquet`
`CBCEvents.csv`	Complete blood count lab events	`cbc_events.parquet`
`ChemistryEvents.csv`	Chemistry lab test results	`chem_events.parquet`
`CultureEvents.csv`	Microbial culture results	`culture_events.parquet`
`FluidBalanceEvents.csv`	Fluid input/output documentation	`fluid_balance_events.parquet`
`HemoEvents.csv`	Hemodynamic monitoring values	`hemo_events.parquet`
`SerologyEvents.csv`	Serological test outcomes	`serology_events.parquet`
`calc_deaths.csv`	Calculated patient mortality data	`calc_deaths.parquet`
`referrals.csv`	Referral information (specialty etc.)	`referrals.parquet`

Notes on Data Quality and Consistency

- **Column Removal**: Columns such as `RowID` and unnamed index columns (e.g., `...1`) were dropped to reduce noise.
- **Wide Format Transformation**: Measurements grouped by name (e.g., `abg_name`, `cbc_name`) were converted into wide format using `pivot_wider()` for one-row-per-timepoint structure.
- **Type Coercion**: Key clinical variables were cast into `double` to ensure numeric operations are consistent.
- **Group-level Missingness Imputation**: `tidyr::fill()` was used within each group (e.g., per `PatientID`) to forward- and backward-fill missing values where reasonable.
- **Deduplication Strategy**: Within each patient-time-event grouping, only the first row was retained using `slice_head()`, assuming earlier rows are most relevant.
- **Group Identifier**: An `opo_group` variable was extracted using the first four characters of `PatientID` to allow stratified subgroup analyses.

Folder Structure and Output Format

- Raw data is located in: `data-raw/physionet.org/files/orchid/2.0.0/`
- Cleaned files are saved to: `data/`
- All output files are written in **Parquet** format using the `nanoparquet::write_parquet()` function for fast I/O and minimal disk usage.

Analysis

Objective 1: Analyze Disparities in Organ Procurement Outcomes

Goal To assess whether organ procurement rates differ across demographic and geographic groups—particularly by race/ethnicity, socioeconomic proxies, and OPO region—and quantify the magnitude and significance of these disparities.

- **Outcome Variable**
  - `organ_procured` (binary): 1 if organ was successfully procured, 0 otherwise.
- **Primary Exposure Variables**
  - **Age**

  - **Gender**
  - **Race**
  - **Organ Procurement Organizations (OPOs)**
- **Covariates (for adjustment)**
  - UNOS defined cause of death
  - UNOS defined mechanism of death
  - UNOS defined circumstances of death
  - Time of referral from hospital

Organ Procurement Outcomes by Demographic, Geographic, and Clinical Characteristics

Table 4 summarizes the baseline characteristics of the study cohort (N = 132,968), stratified by whether an organ was successfully procured. Among all decedents, 9,502 (7.1%) had at least one organ procured, while 123,466 (92.9%) did not.

Age was strongly associated with organ procurement. The median age among those whose organs were not procured was 59 years (IQR: 50–72), compared to 40 years (IQR: 28–54) among those who underwent procurement. Stratified age group analysis revealed that younger patients had higher procurement rates; for instance, decedents aged 20–29 had a procurement rate of 25%, compared to only 16% among those under 18. Procurement likelihood declined progressively with increasing age, suggesting a potential age-related disparity that may reflect clinical ineligibility, comorbidity burden, or differences in referral or donor evaluation practices.

Gender differences in procurement were modest. Males comprised 59% of the cohort and had a procurement rate of 7.5%, compared to 6.7% among females. Although the absolute difference was small, this slight imbalance may stem from anatomical compatibility, clinical profiles, or unmeasured systemic factors. However, without adjustment for clinical variables, it is unclear whether this difference reflects a true disparity or confounding.

Race and ethnicity exhibited more pronounced disparities. White/Caucasian decedents accounted for 60% of the cohort, with a procurement rate of 7.3%. In contrast, Black/African American decedents (19% of the cohort) had a lower procurement rate of 6.1%, while Hispanic decedents (16%) had a notably higher rate of 8.5%. The lower procurement among Black patients may reflect structural inequities in referral, consent, or evaluation processes. Conversely, the relatively high procurement among Hispanic decedents may be influenced by geographic or demographic differences in donor identification and suitability. These trends highlight the importance of adjusting for clinical and regional context in disparity analyses.

Organ Procurement Organization (OPO) performance varied substantially across regions. Procurement rates ranged from 5.3% in OPO3 to 10.2% in OPO5. While differences in case mix may explain some variation, the consistently higher yield in OPO5 suggests operational or procedural differences in donor management and recovery efficiency. Conversely, lower rates in OPOs 2, 3, and 6 may reflect logistical challenges, under-referral, or systemic inefficiencies. These inter-regional disparities underscore the need for standardized performance evaluation and the potential for best-practice dissemination from higher-performing OPOs.

UNOS-defined cause of death was available for 103,207 decedents. Head trauma and cerebrovascular/stroke-related deaths had the highest procurement rates (24% and 26%, respectively), likely reflecting favorable clinical conditions for donation. The most common cause of death—anoxia—had a moderate procurement rate of 9.6%. In contrast, terminal or infectious conditions such as cancer, COPD, HIV, sepsis, and viral disease were associated with near-zero procurement, consistent with contraindications for donation. Notably, no organs were procured from the 29,761 decedents with unknown cause of death, suggesting documentation-related loss of donor opportunities.

UNOS-defined mechanism of death showed similar trends. Among the 98,468 patients with available data, traumatic causes—such as gunshot wounds (32–49%), asphyxiation (30%), and drug intoxication (24–52%)—were associated with the highest procurement rates. Other external causes like blunt trauma, drowning, and electrocution also had elevated rates. In contrast, natural causes, including cardiovascular and unspecified natural deaths, had rates below 6%. These findings reinforce the observation that donation is more likely in settings of sudden trauma, where organ viability can be maintained. The complete absence of procurement in the 34,500 cases with missing mechanism data again raises concern about under-documented opportunities.

UNOS-defined circumstances of death further highlight these patterns. Among decedents with known data (N = 98,524), natural causes accounted for the majority (62%) but had the lowest procurement rate (4.9%). Conversely, deaths from external circumstances such as suicide (32%), homicide (27%), and non-motor vehicle accidents (54%) showed substantially higher procurement rates. Rare categories such as alleged suicide and alleged child abuse—though small in number—had procurement rates exceeding 50%, likely due to younger age and minimal comorbidities. The 34,444 decedents with missing data again had no recorded procurement, highlighting the need for consistent classification of death circumstances to optimize donor recognition.

Hypothesis testing

We hypothesize **whether organ procurement is associated with specific demographic, geographic, or clinical characteristics.**

More specifically, we are tesing the following:

- H_{0} (null): There is no difference in organ procurement rates across the levels of the variable.
- H_{1} (alternative): There is a difference in organ procurement rates across the levels of the variable.

While my initial hypothesis testing plan included both demographic and clinical variables, I am excluding `Cause_of_Death_UNOS`, `Mechanism_of_Death`, and `Circumstances_of_Death` due to evidence of documentation bias. These variables are disproportionately complete among patients whose organs were procured, but often missing or marked as "unknown" for those who were not. Because this documentation typically occurs during or after donor evaluation, the completeness of these fields may be contingent on the procurement process itself. As a result, statistical associations involving these variables may reflect process-related bias rather than true underlying clinical differences.

I also excluded `age_category`, as it is a derived variable from `Age`, which was already included in the analysis using a Welch two-sample t-test. Including both would introduce redundancy and increase the risk of multiple comparisons without providing additional insight.

My final hypothesis testing focused on variables that are consistently recorded and not conditional on procurement activity: `Race`, `Gender`, `OPO`, and continuous `Age`.

variable	method	statistic	p.value
Race	Pearson's Chi-squared test	126.22311	0
Gender	Pearson's Chi-squared test with Yates' continuity correction	29.74435	0
OPO	Pearson's Chi-squared test	516.40130	0
Age	Welch Two Sample t-test	102.93127	0

All variables tested showed statistically significant differences in procurement rates:

- **Race** was significantly associated with procurement status (*x^{2}* = 126, $p < 0.001$), suggesting that procurement rates vary across racial and ethnic groups.
- **Gender** also showed a significant difference (*x^{2}* = 29.7, $p < 0.001$), although the magnitude of the association was smaller.
- **Organ Procurement Organization (OPO)** region was strongly associated with procurement likelihood (*x^{2}* = 516, $p < 0.001$), indicating considerable variation in outcomes across geographic regions.

- **Age**, treated as a continuous variable, was significantly different between procured and non-procured groups (Welch $t = 103$, $p < 0.001$), with younger patients more likely to have organs procured.

These results support the presence of disparities in procurement outcomes related to race, gender, region, and age, motivating further multivariable modeling to quantify these differences while adjusting for potential confounding.

Logistic Regression

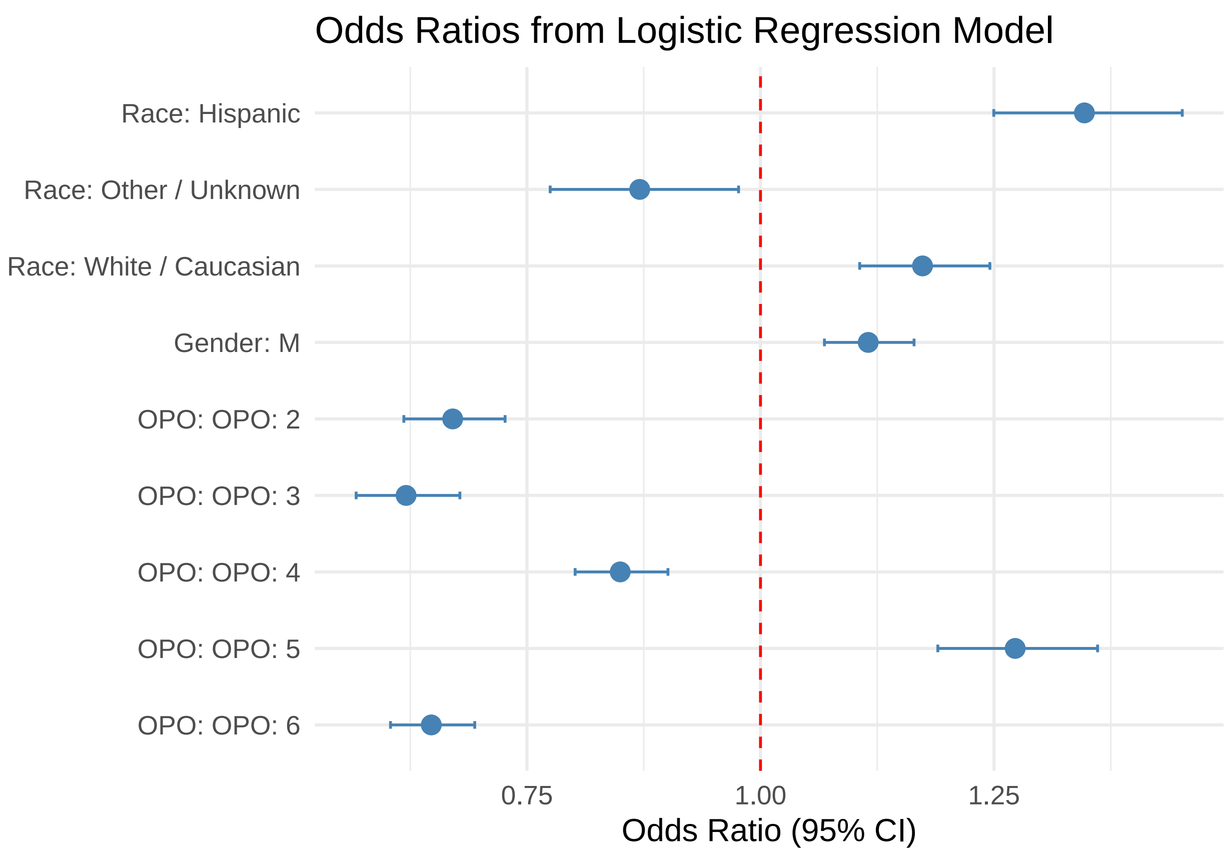
```r
log_reg_model <-
  stats::glm(procured ~ Race + Gender + OPO, data = obj1_abt, family = binomial)

summary(log_reg_model)
```

```
##
## Call:
## stats::glm(formula = procured ~ Race + Gender + OPO, family = binomial,
##     data = obj1_abt)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.5122  -0.4230  -0.3712  -0.3293   2.5564
##
## Coefficients:
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)             -2.61313    0.03426 -76.268  < 2e-16 ***
## RaceHispanic             0.29773    0.03818   7.798 6.29e-15 ***
## RaceOther / Unknown     -0.13846    0.05900  -2.347   0.0189 *
## RaceWhite / Caucasian    0.15999    0.03028   5.284 1.27e-07 ***
## GenderM                  0.10916    0.02194   4.976 6.49e-07 ***
## OPOOPO2                 -0.39976    0.04121  -9.699  < 2e-16 ***
## OPOOPO3                 -0.47711    0.04561 -10.461  < 2e-16 ***
## OPOOPO4                 -0.16271    0.02982  -5.457 4.84e-08 ***
## OPOOPO5                  0.24113    0.03426   7.037 1.96e-12 ***
## OPOOPO6                 -0.43452    0.03549 -12.243  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 68452  on 132967  degrees of freedom
## Residual deviance: 67815  on 132958  degrees of freedom
## AIC: 67835
##
## Number of Fisher Scoring iterations: 5
```

term	estimate	std.error	statistic	p.value	conf.low	conf.high
(Intercept)	0.0733048	0.0342624	-76.268104	0.0000000	0.0685198	0.0783695
RaceHispanic	1.3468028	0.0381810	7.797953	0.0000000	1.2497622	1.4515502
RaceOther / Unknown	0.8706965	0.0590022	-2.346721	0.0189394	0.7748362	0.9765194

term	estimate	std.error	statistic	p.value	conf.low	conf.high
RaceWhite / Caucasian	1.1734948	0.0302799	5.283587	0.0000001	1.1061759	1.2455952
GenderM	1.1153456	0.0219386	4.975901	0.0000006	1.0684655	1.1644221
OPOOPO2	0.6704818	0.0412144	-9.699493	0.0000000	0.6181792	0.7265866
OPOOPO3	0.6205724	0.0456070	-10.461394	0.0000000	0.5671213	0.6781594
OPOOPO4	0.8498368	0.0298171	-5.456965	0.0000000	0.8015663	0.9009546
OPOOPO5	1.2726847	0.0342640	7.037382	0.0000000	1.1898686	1.3609242
OPOOPO6	0.6475777	0.0354920	-12.242669	0.0000000	0.6039110	0.6940658



The figure above displays the adjusted odds ratios (ORs) and 95% confidence intervals from the logistic regression model evaluating associations between demographic/geographic characteristics and the likelihood of organ procurement.

After controlling for all covariates in the model:

- **Race**: Compared to Black patients (reference group), Hispanic patients had **higher odds** of organ procurement (OR is approx. 1.35), while patients categorized as Other/Unknown had **lower odds** (OR is approx. 0.87). White/Caucasian patients also had significantly higher odds (OR is approx. 1.17), suggesting potential racial disparities in procurement outcomes even after adjustment.
- **Gender**: Male patients had **higher odds** of procurement compared to females (OR is approx. 1.12), consistent with patterns observed in the unadjusted analysis.
- **OPO Region**: Substantial geographic variation was observed. Compared to OPO1 (reference), patients in OPO5 had the **highest odds** of procurement (OR is approx. 1.27), while those in OPO2, OPO3, and OPO6 had **significantly lower odds** (ORs ranging from 0.62 to 0.67). These differences may reflect regional variation in practices, infrastructure, or consent processes.

All associations were statistically significant ($p < 0.05$), and none of the confidence intervals included the null value (OR = 1.0). This indicates meaningful adjusted differences in organ procurement across race, gender, and OPO.

Specifically, Hispanic patients, White patients, male patients, and those in OPO5 had significantly higher odds of organ procurement compared to their respective reference groups. In contrast, patients in OPOs 2, 3, 4, and 6 had significantly lower odds.

Appendix

List of Tables

Table 4: Organ Procurement vs. Outcomes

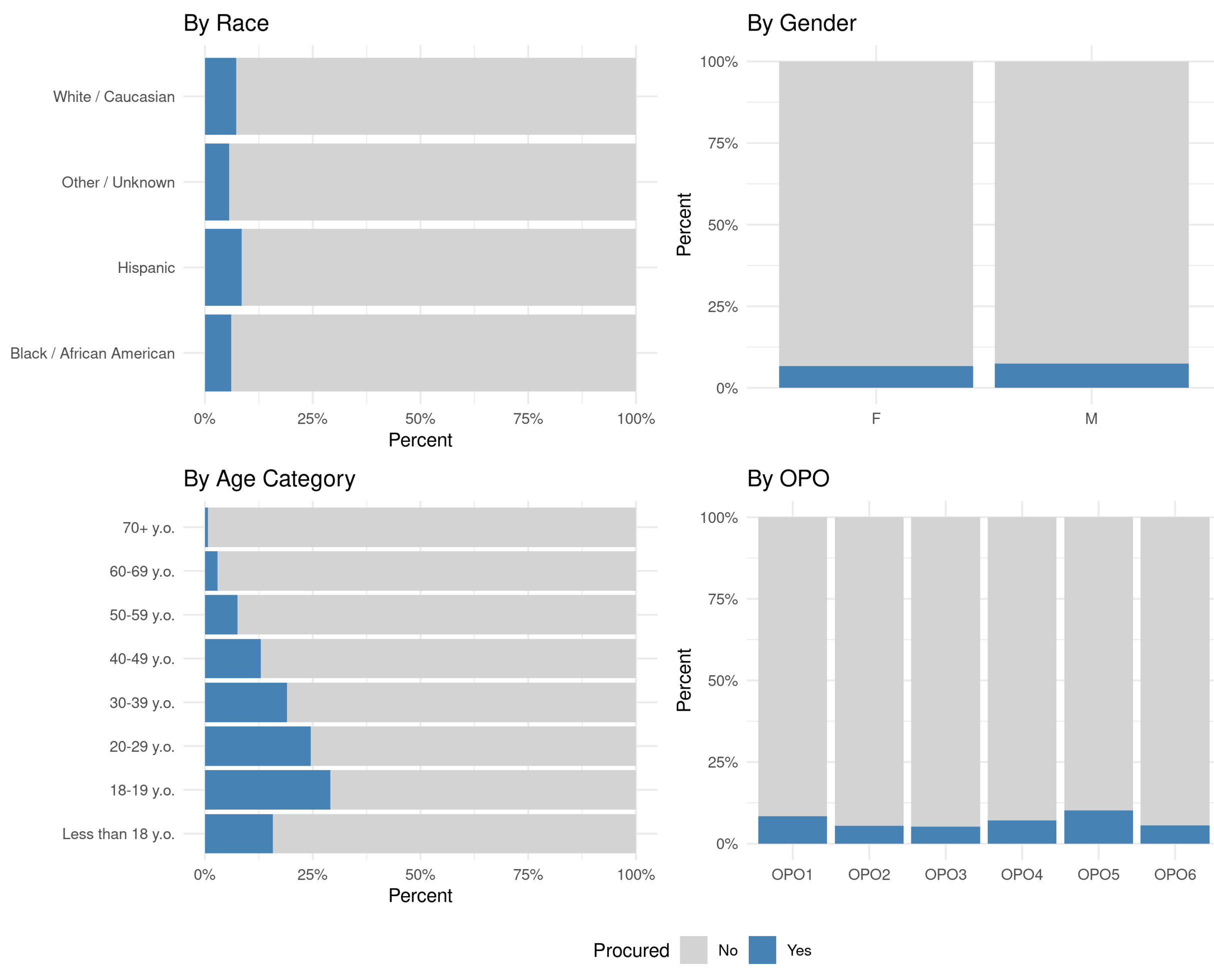
Characteristic	Overall (N = 132968)	Not Procured (N = 123466)	Procured (N = 9502)
Mean Patient Age (IQR)	58 (48, 71)	59 (50, 72)	40 (28, 54)
Age Category - no. (%)			
Less than 18 y.o.	4,535/132,968 (3.4%)	3,819/4,535 (84%)	716/4,535 (16%)
18-19 y.o.	1,112/132,968 (0.8%)	789/1,112 (71%)	323/1,112 (29%)
20-29 y.o.	6,729/132,968 (5.1%)	5,079/6,729 (75%)	1,650/6,729 (25%)
30-39 y.o.	9,607/132,968 (7.2%)	7,781/9,607 (81%)	1,826/9,607 (19%)
40-49 y.o.	13,926/132,968 (10%)	12,119/13,926 (87%)	1,807/13,926 (13%)
50-59 y.o.	25,730/132,968 (19%)	23,795/25,730 (92%)	1,935/25,730 (7.5%)
60-69 y.o.	33,976/132,968 (26%)	32,993/33,976 (97%)	983/33,976 (2.9%)
70+ y.o.	37,353/132,968 (28%)	37,091/37,353 (99%)	262/37,353 (0.7%)
Gender - no. (%)			
M	78,216/132,968 (59%)	72,374/78,216 (93%)	5,842/78,216 (7.5%)
F	54,752/132,968 (41%)	51,092/54,752 (93%)	3,660/54,752 (6.7%)
Race - no. (%)			
White / Caucasian	79,627/132,968 (60%)	73,843/79,627 (93%)	5,784/79,627 (7.3%)
Black / African American	25,155/132,968 (19%)	23,615/25,155 (94%)	1,540/25,155 (6.1%)
Hispanic	20,702/132,968 (16%)	18,942/20,702 (91%)	1,760/20,702 (8.5%)
Other / Unknown	7,484/132,968 (5.6%)	7,066/7,484 (94%)	418/7,484 (5.6%)
Organ Procurement Organization - no. (%)			
OPO4	33,616/132,968 (25%)	31,217/33,616 (93%)	2,399/33,616 (7.1%)
OPO1	32,079/132,968 (24%)	29,382/32,079 (92%)	2,697/32,079 (8.4%)
OPO6	22,905/132,968 (17%)	21,631/22,905 (94%)	1,274/22,905 (5.6%)
OPO2	16,142/132,968 (12%)	15,264/16,142 (95%)	878/16,142 (5.4%)
OPO5	15,725/132,968 (12%)	14,128/15,725 (90%)	1,597/15,725 (10%)
OPO3	12,501/132,968 (9.4%)	11,844/12,501 (95%)	657/12,501 (5.3%)
UNOS defined cause of death - no. (%)			
Anoxia	40,340/103,207 (39%)	36,458/40,340 (90%)	3,882/40,340 (9.6%)
Other	24,248/103,207 (23%)	24,007/24,248 (99%)	241/24,248 (1.0%)
CVA/Stroke	17,577/103,207 (17%)	15,314/17,577 (87%)	2,263/17,577 (13%)
Head Trauma	10,798/103,207 (10%)	8,159/10,798 (76%)	2,639/10,798 (24%)
Infectious Disease - Viral	1,820/103,207 (1.8%)	1,816/1,820 (100%)	4/1,820 (0.2%)
Sepsis	1,763/103,207 (1.7%)	1,759/1,763 (100%)	4/1,763 (0.2%)
Cerebrovascular / Stroke	1,353/103,207 (1.3%)	996/1,353 (74%)	357/1,353 (26%)
Other, specify	736/103,207 (0.7%)	728/736 (99%)	8/736 (1.1%)
Cardiac - Other, specify	701/103,207 (0.7%)	700/701 (100%)	1/701 (0.1%)
Respiratory - Other, specify	679/103,207 (0.7%)	671/679 (99%)	8/679 (1.2%)
ESLD	590/103,207 (0.6%)	585/590 (99%)	5/590 (0.8%)
CNS Tumor	454/103,207 (0.4%)	417/454 (92%)	37/454 (8.1%)
Pneumonia	416/103,207 (0.4%)	410/416 (99%)	6/416 (1.4%)
Cancer	311/103,207 (0.3%)	311/311 (100%)	0/311 (0%)
ICB / ICH	201/103,207 (0.2%)	197/201 (98%)	4/201 (2.0%)
Infectious Disease - Bacterial	155/103,207 (0.2%)	144/155 (93%)	11/155 (7.1%)
AAA or thoracic AA	119/103,207 (0.1%)	118/119 (99%)	1/119 (0.8%)

Table 4: Organ Procurement vs. Outcomes *(continued)*

Characteristic	**Overall** (N = 132968)	**Not Procured** (N = 123466)	**Procured** (N = 9502)
Infectious Disease - Other, specify	114/103,207 (0.1%)	113/114 (99%)	1/114 (0.9%)
CHF	111/103,207 (0.1%)	110/111 (99%)	1/111 (0.9%)
Overdose	88/103,207 (<0.1%)	82/88 (93%)	6/88 (6.8%)
COPD	86/103,207 (<0.1%)	86/86 (100%)	0/86 (0%)
Trauma	84/103,207 (<0.1%)	77/84 (92%)	7/84 (8.3%)
Exsanguination	70/103,207 (<0.1%)	66/70 (94%)	4/70 (5.7%)
ESRD	68/103,207 (<0.1%)	68/68 (100%)	0/68 (0%)
Myocardial infarction	59/103,207 (<0.1%)	54/59 (92%)	5/59 (8.5%)
Pulmonary embolism	55/103,207 (<0.1%)	55/55 (100%)	0/55 (0%)
GSW	47/103,207 (<0.1%)	43/47 (91%)	4/47 (8.5%)
Multi-system failure	45/103,207 (<0.1%)	45/45 (100%)	0/45 (0%)
SAH	29/103,207 (<0.1%)	28/29 (97%)	1/29 (3.4%)
HIV	21/103,207 (<0.1%)	21/21 (100%)	0/21 (0%)
Prematurity	18/103,207 (<0.1%)	18/18 (100%)	0/18 (0%)
Drowning	14/103,207 (<0.1%)	12/14 (86%)	2/14 (14%)
Leukemia / Lymphoma	12/103,207 (<0.1%)	12/12 (100%)	0/12 (0%)
Hepatitis	11/103,207 (<0.1%)	11/11 (100%)	0/11 (0%)
Arrhythmia	9/103,207 (<0.1%)	9/9 (100%)	0/9 (0%)
Fetal Demise	4/103,207 (<0.1%)	4/4 (100%)	0/4 (0%)
Sudden infant death syndrome	1/103,207 (<0.1%)	1/1 (100%)	0/1 (0%)
Unknown	29,761	29,761	0
UNOS defined mechanism of death - no. (%)			
Cardiovascular	27,259/98,468 (28%)	25,599/27,259 (94%)	1,660/27,259 (6.1%)
Natural Causes	25,871/98,468 (26%)	25,555/25,871 (99%)	316/25,871 (1.2%)
ICH/Stroke	16,472/98,468 (17%)	14,184/16,472 (86%)	2,288/16,472 (14%)
None of the Above	8,745/98,468 (8.9%)	8,482/8,745 (97%)	263/8,745 (3.0%)
Blunt Injury	8,297/98,468 (8.4%)	6,458/8,297 (78%)	1,839/8,297 (22%)
Drug Intoxication	3,282/98,468 (3.3%)	2,508/3,282 (76%)	774/3,282 (24%)
Gun Shot Wound	1,984/98,468 (2.0%)	1,345/1,984 (68%)	639/1,984 (32%)
Asphyxiation	1,938/98,468 (2.0%)	1,366/1,938 (70%)	572/1,938 (30%)
Intracranial Hemmorrhage / Stroke	1,311/98,468 (1.3%)	951/1,311 (73%)	360/1,311 (27%)
Death from Natural Causes	890/98,468 (0.9%)	793/890 (89%)	97/890 (11%)
Seizure	775/98,468 (0.8%)	669/775 (86%)	106/775 (14%)
Drug / Intoxication	545/98,468 (0.6%)	264/545 (48%)	281/545 (52%)
Drowning	507/98,468 (0.5%)	390/507 (77%)	117/507 (23%)
Gunshot Wound	297/98,468 (0.3%)	150/297 (51%)	147/297 (49%)
Other	112/98,468 (0.1%)	108/112 (96%)	4/112 (3.6%)
Stab	75/98,468 (<0.1%)	58/75 (77%)	17/75 (23%)
Electrical	51/98,468 (<0.1%)	39/51 (76%)	12/51 (24%)
Sudden Infant Death	41/98,468 (<0.1%)	36/41 (88%)	5/41 (12%)
None of the above	16/98,468 (<0.1%)	11/16 (69%)	5/16 (31%)
Unknown	34,500	34,500	0

Table 4: Organ Procurement vs. Outcomes *(continued)*

Characteristic	**Overall** (N = 132968)	**Not Procured** (N = 123466)	**Procured** (N = 9502)
UNOS defined circumstances of death - no. (%)			
Natural Causes	60,683/98,524 (62%)	57,699/60,683 (95%)	2,984/60,683 (4.9%)
None of the Above	17,841/98,524 (18%)	16,376/17,841 (92%)	1,465/17,841 (8.2%)
Accident, Non-MVA	6,442/98,524 (6.5%)	5,030/6,442 (78%)	1,412/6,442 (22%)
MVA	5,031/98,524 (5.1%)	3,908/5,031 (78%)	1,123/5,031 (22%)
Death from Natural Causes	3,470/98,524 (3.5%)	2,739/3,470 (79%)	731/3,470 (21%)
Suicide	2,279/98,524 (2.3%)	1,539/2,279 (68%)	740/2,279 (32%)
Homicide	1,286/98,524 (1.3%)	933/1,286 (73%)	353/1,286 (27%)
Motor Vehicle Accident	480/98,524 (0.5%)	252/480 (53%)	228/480 (48%)
Non-Motor Vehicle Accident	336/98,524 (0.3%)	155/336 (46%)	181/336 (54%)
Alleged Suicide	293/98,524 (0.3%)	138/293 (47%)	155/293 (53%)
Alleged Homicide	141/98,524 (0.1%)	66/141 (47%)	75/141 (53%)
Child Abuse	127/98,524 (0.1%)	92/127 (72%)	35/127 (28%)
Other	95/98,524 (<0.1%)	86/95 (91%)	9/95 (9.5%)
Alleged Child Abuse	20/98,524 (<0.1%)	9/20 (45%)	11/20 (55%)
Unknown	34,444	34,444	0


By Race
White / Caucasian
Other / Unknown
Hispanic
Black / African American
0%
25%
50%
75%
100%
Percent
By Gender
100%
75%
50%
25%
0%
Percent
F
M
By Age Category
70+ y.o.
60-69 y.o.
50-59 y.o.
40-49 y.o.
30-39 y.o.
20-29 y.o.
18-19 y.o.
Less than 18 y.o.
0%
25%
50%
75%
100%
Percent
By OPO
100%
75%
50%
25%
0%
Percent
OPO1
OPO2
OPO3
OPO4
OPO5
OPO6
Procured
No
Yes