

Evidence of Racial Profiling by the Austin Police Department in 2020*

Benny Rochwerger

April 18, 2024

This report investigated the City of Austin, Texas ‘2020 Racial Profiling (RP) dataset’ and a Bayesian logistic regression model was created to assess the effect of an individual’s sex, race, and whether a search was performed on the probability of undergoing a custody arrest. This analysis suggested that, in part, approximately 46%, 32%, and 21% of individuals arrested were Hispanic or Latino, White, and Black, respectively, and that Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset had a greater likelihood of undergoing a custody arrest relative to a White individual. These findings signify that Hispanic or Latino and Black individuals were overrepresented among the arrests in this dataset and that the impacts of policing on Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals should be examined in greater detail in the United States. Future research could examine combinations of predictors or whether custody arrests are associated with other factors, such as geographical location and income level.

Table of contents

1	Introduction	2
2	Data	3
3	Model	7
3.1	Model set-up	7
3.2	Model justification	8
4	Results	9

*Data and code employed in the creation of this report can be found here: <https://github.com/bennyrochwerger/profiling>

5	Discussion	9
5.1	Hispanic or Latino and Black individuals were overrepresented among the arrests in this dataset	11
5.2	Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset had a greater likelihood of undergoing a custody arrest relative to a White individual	11
5.3	Weaknesses	12
5.4	Next steps	12
A	Appendix	14
A.1	Sketches	14
A.2	Simulation	14
A.3	Tests	14
A.4	Model details	14
	A.4.1 Posterior predictive check and comparison of the prior and posterior . .	14
	A.4.2 Diagnostics	14
A.5	Credibility intervals	16
A.6	Styling of code	16
	References	18

1 Introduction

The term “racial profiling” describes race- or skin colour-based, instead of evidence-based, suspicion by those such as police officers that a crime was carried out by an individual (Oxford Learner’s Dictionaries, n.d.). For example, based on law enforcement data, it has been reported that the Black and Hispanic populations in California, United States experience racial profiling (Dorsey 2024). Racial profiling has far-reaching consequences; for instance, it has been reported as being possibly detrimental to health and may give rise to post-traumatic stress disorder (Hardman 2019). Trust between community and police has also been reported as being put under pressure by profiling (Natarajan 2014).

Custody arrests from UT (or University of Texas; “The University of Texas System” (n.d.)) police motor vehicle stops have been previously examined (Waller 2018). Also, possession of marijuana-related custody arrests by the APD (or the Austin Police Department; “Public Information Office” (n.d.)) have been reported to predominantly comprise Hispanic and African American individuals (based on Curtin (2019)). However, the relationship between race and APD custody arrests as a whole does not appear to have been examined in detail. Consequently, this report analyzes the City of Austin, Texas “2020 Racial Profiling (RP) dataset” (Austin Police Department 2023a) to model the effect of an individual’s sex, race, and whether a search was performed on the probability of undergoing a custody arrest. That is, the true

effects of sex, race, and whether a search was performed on the outcome of experiencing a custody arrest represent the estimand in this analysis (based on Alexander (2023)).

This report investigated the City of Austin, Texas “2020 Racial Profiling (RP) dataset” (Austin Police Department 2023a), as described in Section 2. To model the effect of an individual’s sex, race, and whether a search was performed on the probability of undergoing a custody arrest, a Bayesian logistic regression model was created (Section 3). This analysis suggested that, in part, approximately 46%, 32%, and 21% of individuals arrested were Hispanic or Latino, White, and Black, respectively (Section 2), and that Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset had a greater likelihood of undergoing a custody arrest relative to a White individual (based on Alexander (2023) and Nahhas (2024); Section 4 and Section A). These findings signify that Hispanic or Latino and Black individuals were overrepresented among the arrests in this dataset and that the impacts of policing on Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals should be examined in greater detail in the United States (Section 5). Also, the dataset (Austin Police Department 2023a) could be used for a future geographical analysis of custody arrests to examine whether certain areas are over-policed or more racially profiled. Furthermore, future research could assess whether there is a relationship between the prevalence of custody arrests and socioeconomic factors such as income level, and combinations of predictors could be employed rather than individual predictors.

Overall, this paper includes Section 2 (which contains an overview of the dataset and the variables employed in this analysis), Section 3 (which describes and justifies the model produced in this report), Section 4 (which includes the results of the model), Section 5 (where outcomes of this investigation, weaknesses, and next steps are discussed), and Section A (which includes additional information such as model details).

2 Data

In this report, the City of Austin, Texas “2020 Racial Profiling (RP) dataset” will be analyzed (Austin Police Department 2023a). This dataset comprises 68,552 entries (Austin Police Department 2023b) on 2020 Austin Police Department traffic stop-based arrests, warnings or field observations, and citations (Austin Police Department 2023a). This indicates how the variables were measured for storage in this dataset. In addition, this dataset was made available on the City of Austin’s Open Data Portal, which is run by the Communications and Technology Management Department’s Open Data Team (City of Austin, Texas, n.d.a). The City of Austin’s Open Data Portal’s website indicates that public data usage is supported in part to make the government more transparent (City of Austin, Texas, n.d.a).

This analysis will focus on the following variables from this dataset (Austin Police Department 2023a): 1) “TCOLE Sex”, which includes classifications of female and male; 2) “Standardized Race”, which separates “Asian” from “Hawaiian-Pacific Islander” and “Middle Eastern”; 3) “Search Yes or No”, which indicates whether a search was performed; and 4) “Custody”, which

is only applicable to arrest stops and states whether an arrest was non-custody or custody in nature (Austin Police Department 2023c).

One similar dataset was the City of Toronto “Police Race and Identity Based Data - Use of Force” dataset (Toronto Police Services 2022). However, with respect to data analysis based on race, the description of this dataset indicates that the data does not include routine traffic stops (Toronto Police Services 2022). Consequently, this dataset was not employed in this report.

The data was downloaded using the R programming language (R Core Team 2023) as well as the `tidyverse` package (Wickham et al. 2019). Next, the data was cleaned with the R programming language (R Core Team 2023) as well as the `tidyverse` (Wickham et al. 2019) and `arrow` (Richardson et al. 2024) packages. The cleaning process also involved creating variables that denoted whether someone was male, female, Asian, Black, White, Hawaiian/Pacific Islander, Middle Eastern, Hispanic or Latino, or American Indian/Alaskan Native as well as variables that signified whether a search was performed and whether an arrest was non-custody or custody in nature. Afterward, the data was loaded using the R programming language (R Core Team 2023) as well as the `arrow` (Richardson et al. 2024) and `here` (Müller 2020) packages. To generate the graphs in Section 2, the R programming language (R Core Team 2023) as well as the `tidyverse` package (Wickham et al. 2019) were employed. Summary statistics (i.e., percentages) are shown in several of these graphs, and these graphs illustrate the variables and observations to be analyzed.

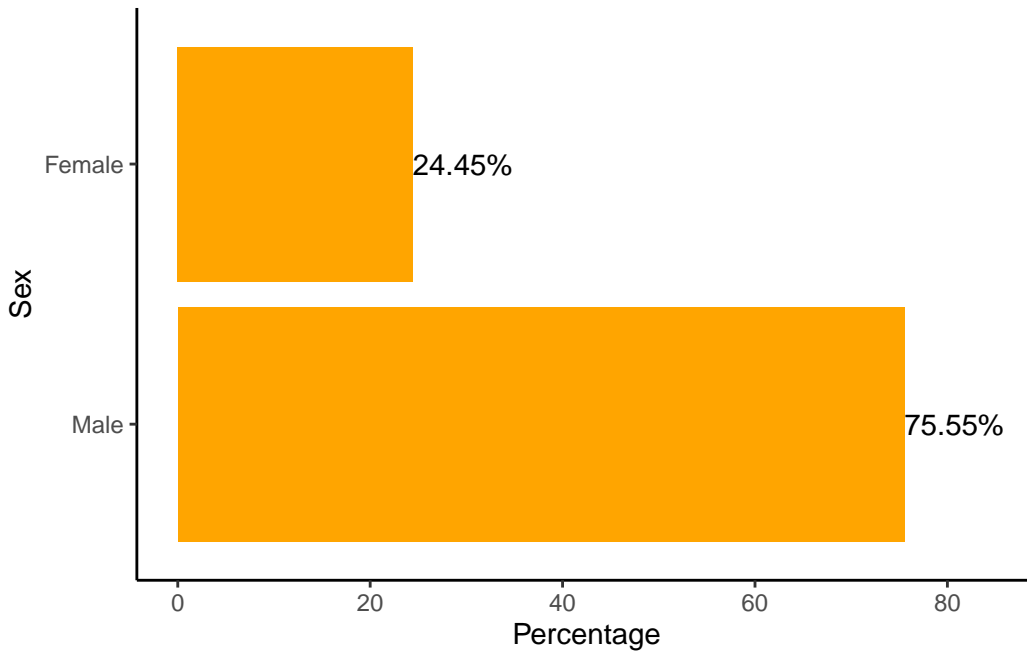


Figure 1: Sexes of those arrested from 2020 traffic stops by the APD

Figure 1 depicts that approximately 76% of individuals arrested based on traffic stops by the Austin Police Department in 2020 were male, while approximately 24% were female.

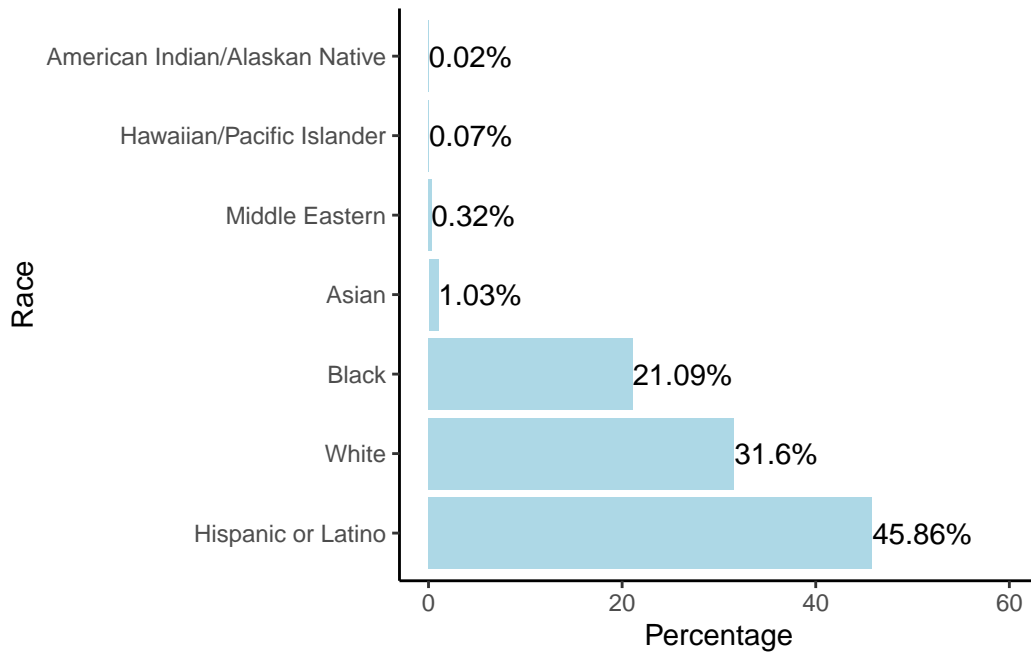


Figure 2: Races of those arrested from 2020 traffic stops by the APD

Figure 2 illustrates the races of individuals arrested based on traffic stops by the Austin Police Department in 2020. Approximately 46% of individuals arrested were Hispanic or Latino, followed by White (approximately 32%), Black (approximately 21%), Asian (approximately 1%), and Middle Eastern, Hawaiian/Pacific Islander, or American Indian/Alaskan Native (less than 0.5% combined).

Figure 3 shows that a search was performed for approximately 89% of individuals arrested based on traffic stops by the Austin Police Department in 2020. Conversely, a search was not performed for approximately 11% of individuals arrested.

Figure 4 illustrates that approximately 90% of individuals arrested based on traffic stops by the Austin Police Department in 2020 experienced a custody arrest, while approximately 10% experienced a non-custody arrest.

Using code adapted from Alexander (2023), Figure 5 was created. Figure 5 depicts the arrest form of individuals arrested based on traffic stops by the Austin Police Department in 2020 by sex and race. It appears that among females, custody arrests were most prevalent among White individuals, followed by Hispanic or Latino individuals and Black individuals. Conversely, among males, custody arrests were most prevalent among Hispanic or Latino individuals, followed by White individuals and Black individuals.

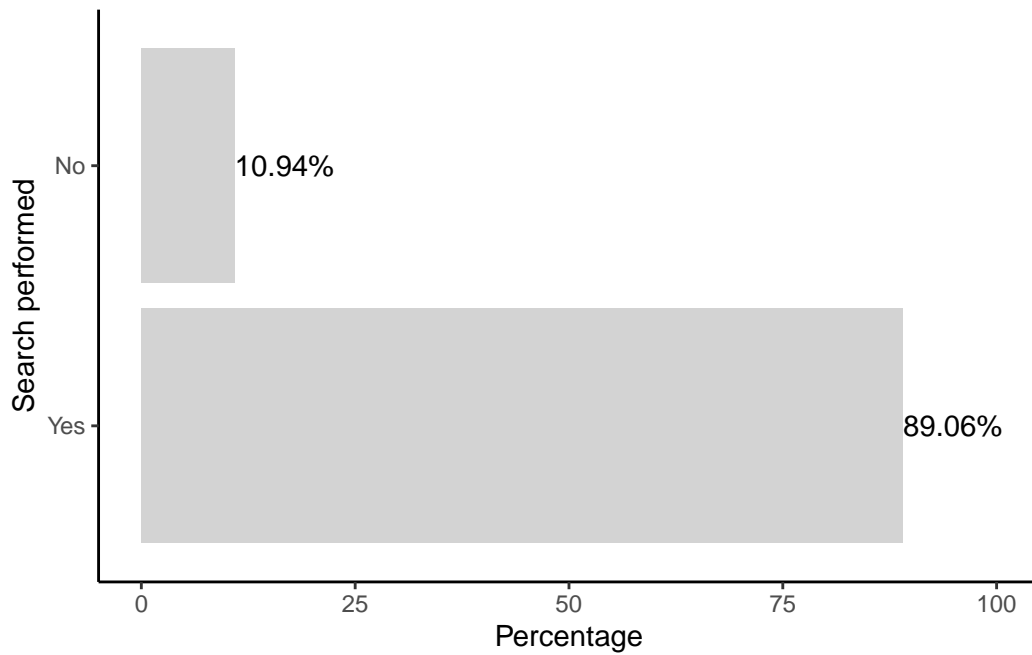


Figure 3: Searches of those arrested from 2020 traffic stops by the APD

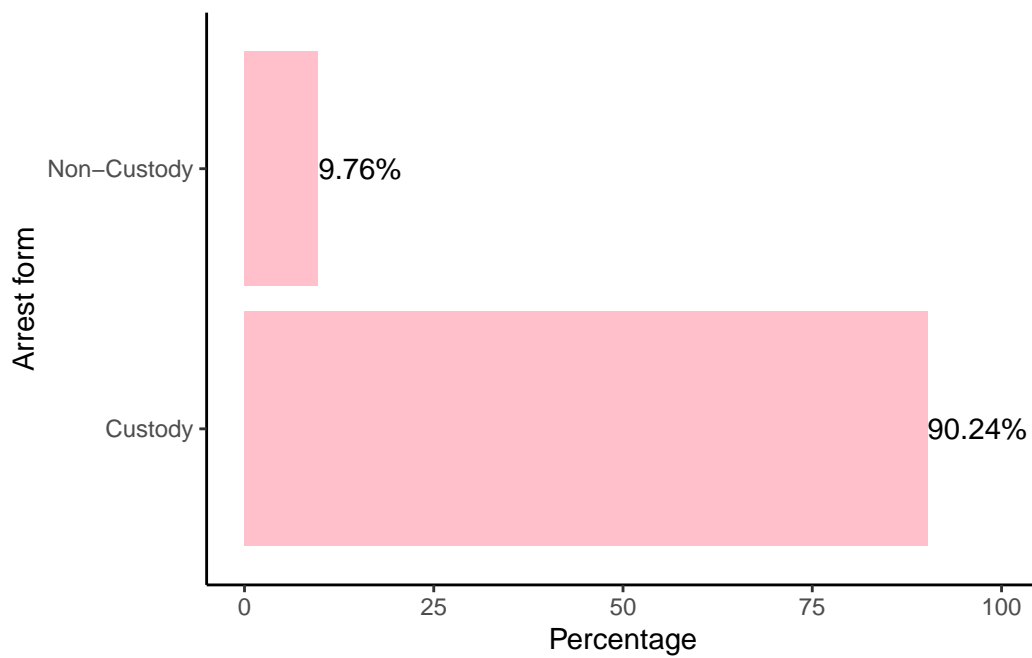


Figure 4: Arrest form from 2020 traffic stops by the APD

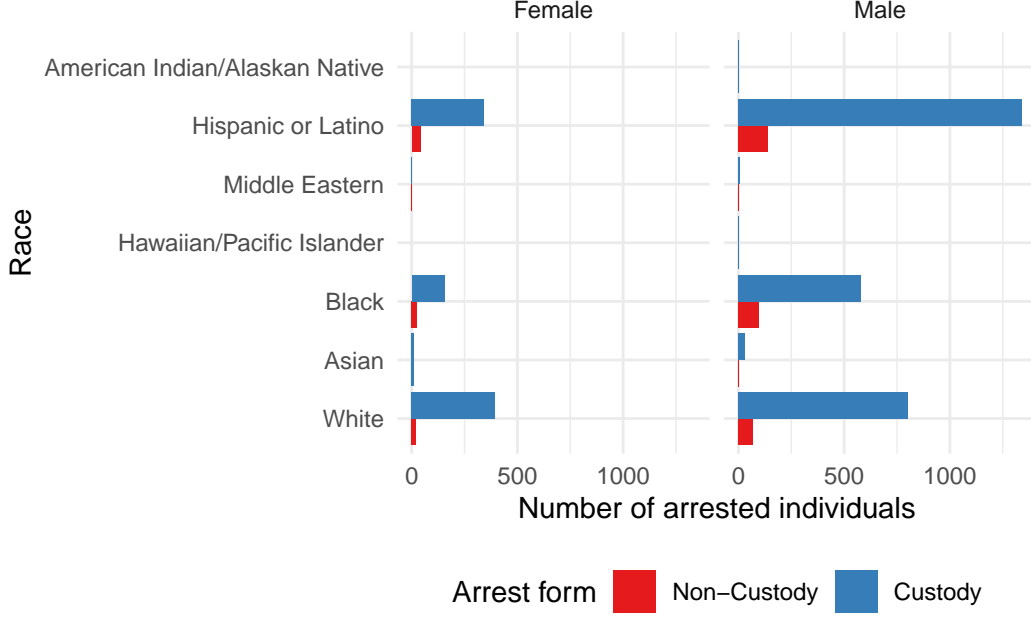


Figure 5: Arrest form from 2020 traffic stops by the APD by sex and race

3 Model

In order to gain insight into potential racial profiling based on 2020 Austin Police Department traffic stop-based arrests (Austin Police Department 2023a), a model was created. In particular, this model involved logistic regression, which was suitable because the outcome variable of interest (i.e., whether or not an individual underwent a custody arrest) was binary in nature (Alexander 2023). Also, this model was Bayesian, meaning that the model parameters follow probability distributions (Alexander 2023). A prior or initial probability distribution must be chosen for the parameters in advance of a Bayesian regression (Alexander 2023); the priors used in this model are described in Section 3.1.

3.1 Model set-up

$$y_i | \pi_i \sim \text{Bern}(\pi_i) \quad (1)$$

$$\text{logit}(\pi_i) = \beta_0 + \beta_1 \times \text{sex}_i + \beta_2 \times \text{race}_i + \beta_3 \times \text{search}_i \quad (2)$$

$$\beta_0 \sim \text{Normal}(0, 2.5) \quad (3)$$

$$\beta_1 \sim \text{Normal}(0, 2.5) \quad (4)$$

$$\beta_2 \sim \text{Normal}(0, 2.5) \quad (5)$$

$$\beta_3 \sim \text{Normal}(0, 2.5) \quad (6)$$

The Bayesian logistic regression model is represented by Equations 1, 2, 3, 4, 5, and 6 (adapted from Alexander (2023)). In these equations, y_i represents the individual’s arrest form (i.e., 0 for a non-custody arrest or 1 for a custody arrest; based on Alexander (2023)), π_i represents the probability of the i th observation being a custody arrest (based on Alexander (2023)), β_0 represents the intercept (or the log-odds of a custody arrest for a female, White, non-searched individual; based on Nahhas (2024)), β_1 represents how much the log-odds of a custody arrest change on average depending on the sex of the individual (relative to a female individual; based on Alexander (2023) and Nahhas (2024)), sex_i represents the sex of the i th individual (based on Alexander (2023)), β_2 represents how much the log-odds of a custody arrest change on average depending on the race of the individual (relative to a White individual; based on Alexander (2023) and Nahhas (2024)), race_i represents the race of the i th individual (based on Alexander (2023)), β_3 represents how much the log-odds of a custody arrest change on average depending on whether a search was performed (relative to a non-searched individual; based on Alexander (2023) and Nahhas (2024)), and search_i represents the search status of the i th individual (i.e., whether or not a search was performed; based on Alexander (2023)).

Given the above description, the β coefficients are important because they can yield insight regarding the effect of an individual’s sex, race, and search status on their likelihood of experiencing a custody arrest.

3.2 Model justification

As described previously, logistic regression was used because the outcome variable of interest (i.e., whether or not an individual experienced a custody arrest) was binary in nature (Alexander 2023). Given that a higher percentage of Black men than Black women have been reported as experiencing unfair police stopping due to their ethnicity or race (DeSilver, Lipka, and Fahmy 2020), individuals’ race and sex were included in this model. In addition, from an intuitive perspective, the occurrence of a search may increase the likelihood of a custody arrest, so a positive coefficient may be expected for a search status of “Yes” (Austin Police Department 2023a). One weakness of this model is that certain variables, such as the ages of the individuals under arrest, were not provided (Austin Police Department 2023a). This could have potentially been a useful addition to the model as it may have offered further insight into the factors that are linked to a higher likelihood of experiencing a custody arrest. Additional weaknesses of this analysis are explored in Section 5.3.

With respect to alternative potential models, linear regression was not used because it can produce outcomes that lie outside the range in between the numbers 0 and 1 (i.e., outside of the possible values of a probability; based on Alexander (2023)). In addition, Poisson regression was not employed because the outcome variable of interest (i.e., whether or not an individual experienced a custody arrest) is not an integer count variable (Alexander 2023).

The `rstanarm` package (Goodrich et al. 2024) and the R programming language (R Core Team 2023) were employed in order to run this model. The `rstanarm` (Goodrich et al. 2024)

default priors were utilized and are reflected in Equations 3, 4, 5, and 6. Using the data as a foundation, the `rstanarm` package (Goodrich et al. 2024) scaled the priors (Alexander 2023). Section A.4 contains a posterior predictive check and diagnostics for this model (Alexander 2023).

4 Results

With the help of code adapted from Alexander (2023), the `modelsummary` package (Arel-Bundock 2022) was used to create Table 1, Figure 10, and Figure 11. Table 1 displays a summary of the results of this model, and Figure 10 and Figure 11 depict 90% credibility intervals of predictors of undergoing a custody arrest based on the model from this report.

This model’s results indicate that the intercept (β_0) is positive (i.e., the 90% credibility interval lies above 0 as per Figure 11), suggesting that the log-odds of a custody arrest for a female, White, non-searched individual (based on Nahhas (2024)) are positive according to this dataset. In addition, the male sex coefficient’s 90% credibility interval includes 0 (Figure 11), so there does not appear to be a link between being male and a higher or lower likelihood of experiencing a custody arrest as per this dataset. Similarly, the Asian race coefficient’s 90% credibility interval includes 0 (Figure 11), so there does not appear to be an association between being Asian and a greater or smaller likelihood of undergoing a custody arrest according to this dataset.

Moreover, the Black, Middle Eastern, and Hispanic or Latino race coefficients’ 90% credibility intervals lie below 0 (Figure 11), suggesting that Black, Middle Eastern, and Hispanic or Latino individuals in this dataset had a lower likelihood of experiencing a custody arrest relative to a White individual (based on Alexander (2023) and Nahhas (2024)). Conversely, the Hawaiian/Pacific Islander and American Indian/Alaskan Native race coefficients’ 90% credibility intervals lie substantially above 0 (Figure 10), indicating that Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset had a greater likelihood of undergoing a custody arrest relative to a White individual (based on Alexander (2023) and Nahhas (2024)).

Furthermore, the 90% credibility interval for the coefficient of a search being performed lies above 0 (Figure 11), suggesting that the occurrence of a search was associated with a greater likelihood of experiencing a custody arrest.

5 Discussion

This report analyzed the City of Austin, Texas “2020 Racial Profiling (RP) dataset” (Austin Police Department 2023a) by graphing variables from the dataset (Section 2) and using a

Table 1: Modeling the likelihood of a person to undergo a custody arrest

	Undergo a custody arrest
(Intercept)	1.037 (0.167)
sexMale	−0.020 (0.133)
raceAsian	1.122 (1.144)
raceBlack	−0.859 (0.153)
raceHawaiian/Pacific Islander	57.921 (52.851)
raceMiddle Eastern	−1.527 (0.738)
raceHispanic or Latino	−0.370 (0.135)
raceAmerican Indian/Alaskan Native	103.105 (91.776)
searchYes	2.008 (0.125)
Num.Obs.	4069
R2	0.098
Log.Lik.	−1161.497
ELPD	−1170.4
ELPD s.e.	40.7
LOOIC	2340.9
LOOIC s.e.	81.4
WAIC	2338.8
RMSE	0.28

Bayesian logistic regression model to examine predictors of undergoing a custody arrest (Section 3 and Section 4). In particular, these predictors were an individual’s sex, race, and whether a search was performed.

5.1 Hispanic or Latino and Black individuals were overrepresented among the arrests in this dataset

Section 2 and Figure 2 revealed that approximately 46% of individuals arrested based on traffic stops by the Austin Police Department in 2020 were Hispanic or Latino, followed by White (approximately 32%), Black (approximately 21%), Asian (approximately 1%), Middle Eastern (approximately 0.32%), Hawaiian/Pacific Islander (approximately 0.07%), and American Indian/Alaskan Native (approximately 0.02%).

However, in 2020, the City of Austin, Texas was comprised of 47.1% White, Non-Hispanic individuals, 32.5% Hispanic or Latino individuals, 8.9% Asian, Non-Hispanic individuals, 6.9% Black or African American, Non-Hispanic individuals, 3.9% Non-Hispanic individuals with two or more races, 0.2% American Indian & Alaska Native, Non-Hispanic individuals, 0.1% Native Hawaiian & Other Pacific Islander, Non-Hispanic individuals, and 0.5% Non-Hispanic individuals with a different race (Valencia 2021). This suggests that White (approximately 32% versus 47.1%), Asian (approximately 1% versus 8.9%), Hawaiian/Pacific Islander (approximately 0.07% versus 0.1%), and American Indian/Alaskan Native (approximately 0.02% versus 0.2%) individuals were underrepresented in the arrest data compared to Austin at large, while Hispanic or Latino (approximately 46% versus 32.5%) and Black (approximately 21% versus 6.9%) individuals were overrepresented (Valencia 2021).

While racial profiling may be a factor in the overrepresentation of Hispanic or Latino and Black individuals among the arrests in this dataset, the dataset itself (Austin Police Department 2023a) may not be completely accurate. For instance, the dataset’s description states that “The data provided are for informational use only and may differ from official APD crime data” (Austin Police Department 2023a), suggesting that this dataset may not be reflective of the true nature of 2020 Austin Police Department traffic stop-based arrests, warnings or field observations, and citations (Austin Police Department 2023a). Consequently, this overrepresentation may be a result of the data that ended up in the final dataset, which may or may not align with the true practices of the Austin Police Department.

5.2 Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset had a greater likelihood of undergoing a custody arrest relative to a White individual

The results of the logistic regression model employed in this report (Section 3 and Section 4) suggested that Black, Middle Eastern, and Hispanic or Latino individuals in this dataset had a lower likelihood of experiencing a custody arrest relative to a White individual (based

on Alexander (2023) and Nahhas (2024)), while Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset had a greater likelihood of undergoing a custody arrest relative to a White individual (based on Alexander (2023) and Nahhas (2024)).

Although analysis of race and policing has appeared to emphasize the impacts on Black and Latino individuals (e.g., Poston and Chang (2019) and Choudhury (2018)), Indigenous people (such as Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals) in the United States do not seem to be a primary focus. As a result, the greater likelihood of undergoing a custody arrest relative to a White individual (based on Alexander (2023) and Nahhas (2024)) among Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals in this dataset suggests that the impacts of policing on these populations should be examined more closely in the United States.

5.3 Weaknesses

One weakness of this analysis was the possibility that the data in the dataset was not fully accurate. That is, the dataset’s website states that “The data provided are for informational use only and may differ from official APD crime data” (Austin Police Department 2023a). In addition, the City of Austin’s Open Data Portal’s Terms of Use states that “THE CITY OF AUSTIN MAKES NO REPRESENTATIONS OR WARRANTY AS TO THE COMPLETENESS, ACCURACY, QUALITY, TIMELINESS, CONTENT, OR ANY OTHER ASPECT OF ANY DATA MADE AVAILABLE THROUGH THIS SITE” (City of Austin, Texas, n.d.b). This suggests that the results obtained in this report may not fully reflect the true practices of the Austin Police Department.

In addition, another weakness of this report is that combinations of predictors (e.g., Black males where a search was performed, White females where a search was not performed, etc.) were not incorporated into the logistic regression model. This could have provided more specific information about groups of factors that are associated with undergoing a custody arrest (e.g., American Indian/Alaskan Native males where a search was not performed), rather than the effects of individual variables (i.e., an individual’s sex, race, and search status) on this outcome variable.

5.4 Next steps

Future research could assess whether there is a relationship between the prevalence of custody arrests and socioeconomic factors such as income level. In addition, the dataset (Austin Police Department 2023a) could be used for a geographical analysis of custody arrests, such as by zip code or county, for purposes such as examining whether certain areas are over-policed or more racially profiled. Additionally, a model could be constructed using combinations of predictors (e.g., Middle Eastern females where a search was not performed) rather than individual predictors (i.e., an individual’s sex, race, and search status) to gain further insight

into the factors that are associated with undergoing a custody arrest. Moreover, the impacts of policing on Hawaiian/Pacific Islander and American Indian/Alaskan Native individuals should be examined in greater detail in the United States to learn more about these particular populations, especially given the wide 90% credibility intervals observed for these races in this report.

A Appendix

A.1 Sketches

Data, graph, and analysis sketches can be found in this report’s GitHub Repository.

A.2 Simulation

A data simulation script can be found in this report’s GitHub Repository and was created with the R programming language (R Core Team 2023) as well as the `tidyverse` (Wickham et al. 2019) and `janitor` (Firke 2023) packages.

A.3 Tests

Scripts with code used for testing can be found in this report’s GitHub Repository. The R programming language (R Core Team 2023) as well as the `tidyverse` package (Wickham et al. 2019) were used to test the real and simulated data.

A.4 Model details

A.4.1 Posterior predictive check and comparison of the prior and posterior

Using code adapted from Alexander (2023), a posterior predictive check was performed (Figure 6). Figure 6 illustrates a comparison between posterior distribution simulations and the actual probability of experiencing a custody arrest (based on Alexander (2023)).

In addition, using code adapted from Alexander (2023), a comparison of the prior and posterior was performed (Figure 7). Figure 7 depicts the amounts by which the estimates are modified after considering data (Alexander 2023).

A.4.2 Diagnostics

This section assesses whether the `rstanarm` (Goodrich et al. 2024) Markov chain Monte Carlo (MCMC) algorithm experienced problems (Alexander 2023).

Using code adapted from Alexander (2023), a trace plot was generated (Figure 8). Figure 8 illustrates horizontal lines that are seemingly erratic with chain overlap, indicating nothing unusual (based on Alexander (2023)).

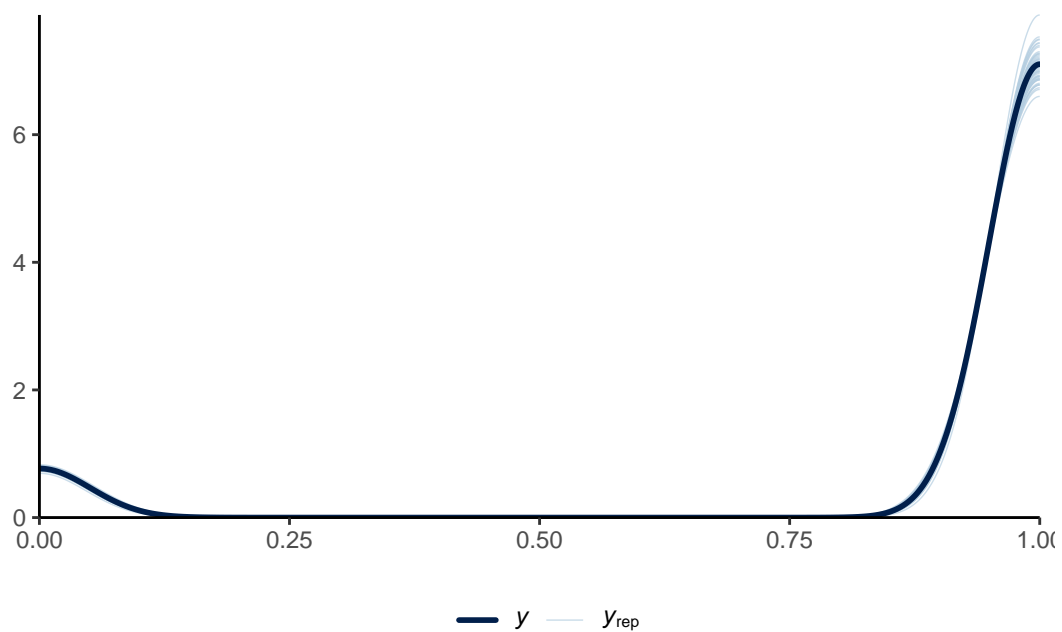


Figure 6: Posterior predictive check

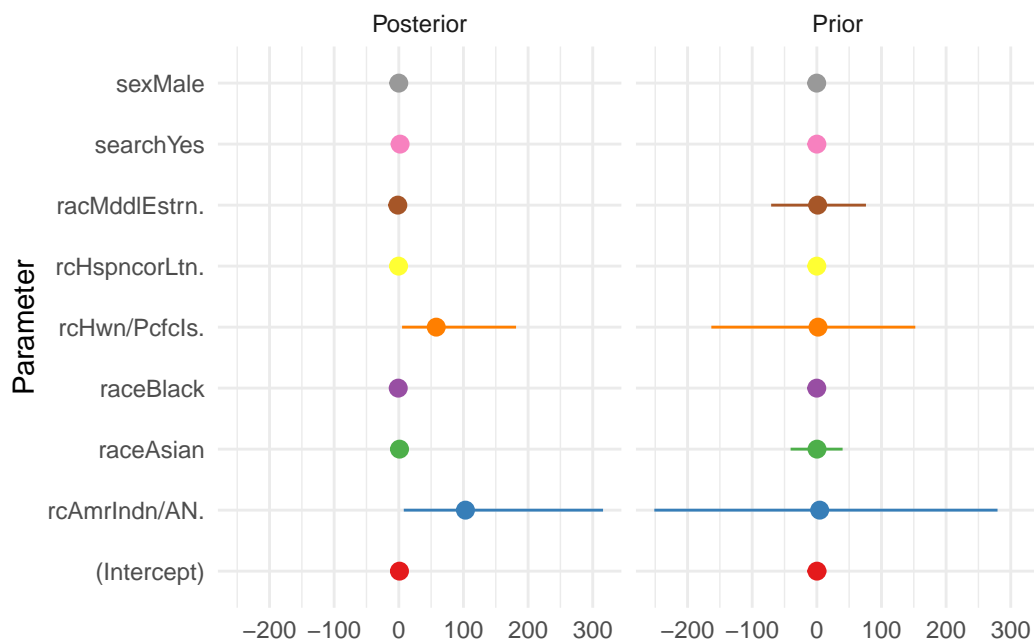


Figure 7: Comparison of the prior and posterior

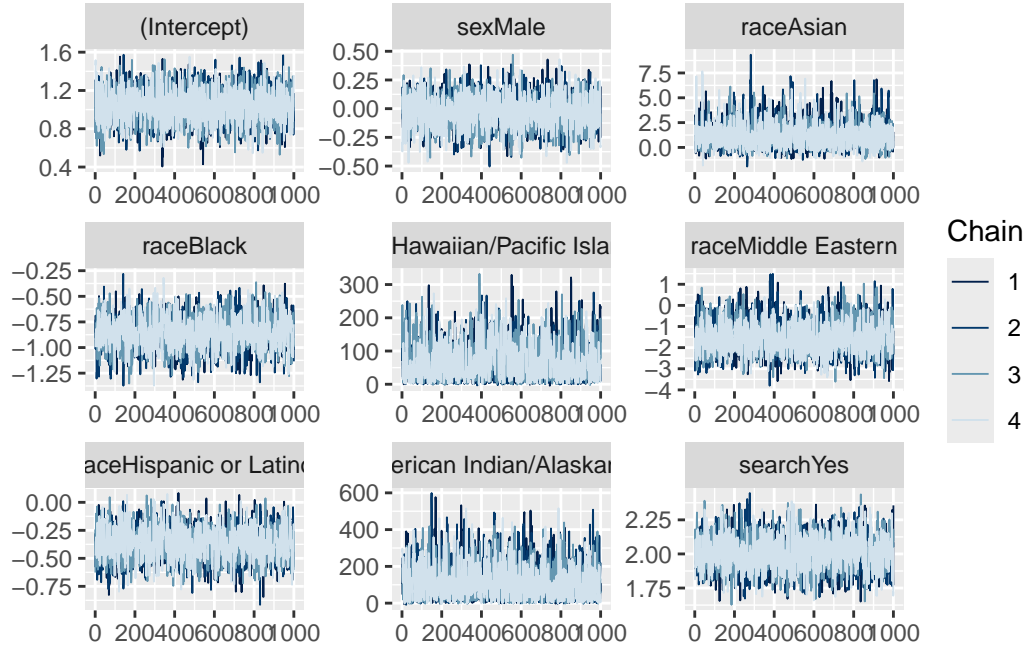


Figure 8: Trace plot

Moreover, using code adapted from Alexander (2023), a Rhat plot was created (Figure 9). Figure 9 depicts values near 1 and less than or equal to 1.1, indicating no issues (based on Alexander (2023)).

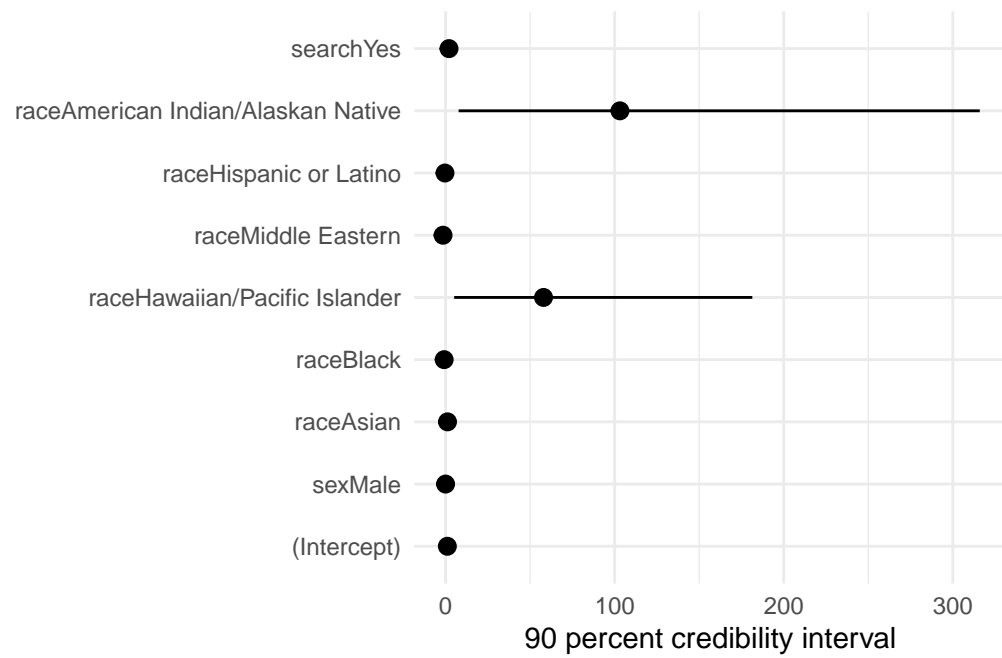
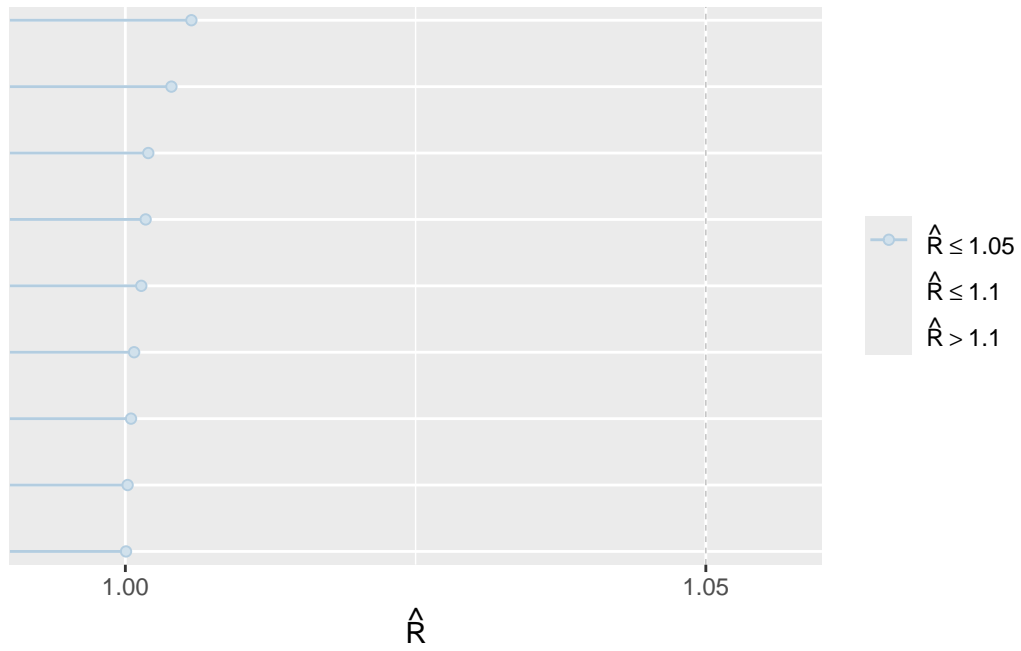
A.5 Credibility intervals

Using code adapted from Alexander (2023), Figure 10 was generated. Figure 10 illustrates 90% credibility intervals of all of the predictors of undergoing a custody arrest based on the model from this report.

Figure 11 depicts 90% credibility intervals of several of the predictors of undergoing a custody arrest. In particular, the American Indian/Alaskan Native and Hawaiian/Pacific Islander predictors were omitted for visual clarity (as compared to Figure 10).

A.6 Styling of code

Code was styled using the `lintr` package (Hester et al. 2024) for the R programming language (R Core Team 2023).



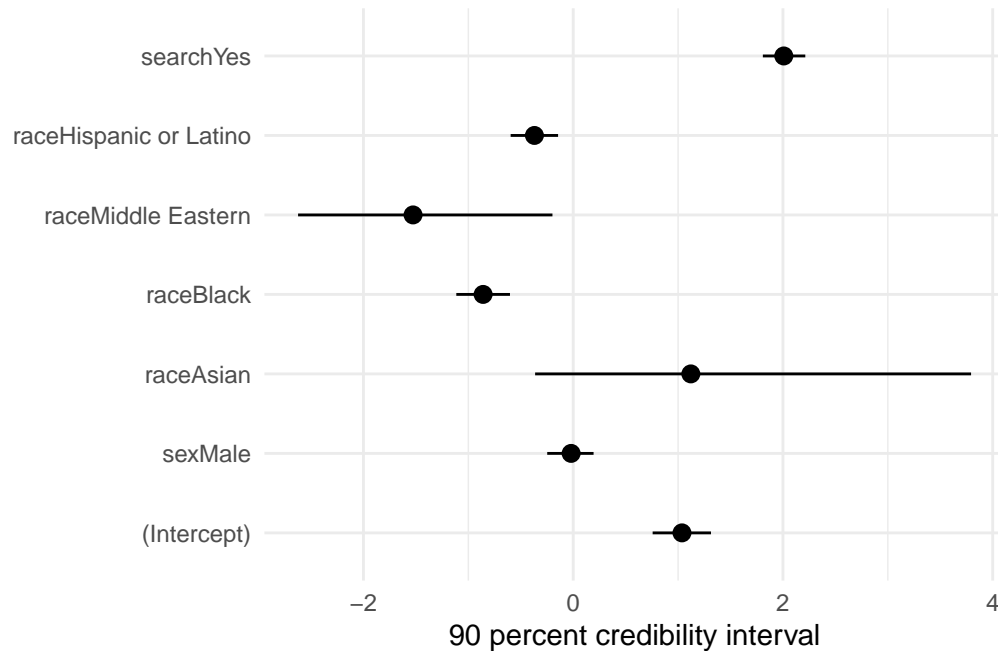


Figure 11: Credibility intervals of several of the custody arrest predictors

References

- Alexander, Rohan. 2023. *Telling Stories with Data*. Boca Raton: CRC Press. <https://tellingstorieswithdata.com/>.
- Arel-Bundock, Vincent. 2022. “modelsummary: Data and Model Summaries in R.” *Journal of Statistical Software* 103 (1): 1–23. <https://doi.org/10.18637/jss.v103.i01>.
- Austin Police Department. 2023a. “2020 Racial Profiling (RP) Dataset.” City of Austin, Texas Open Data Portal. https://data.austintexas.gov/Public-Safety/2020-Racial-Profiling-RP-dataset/c65h-gw3m/about_data.
- . 2023b. “2020 Racial Profiling (RP) Dataset.” City of Austin, Texas Open Data Portal. https://data.austintexas.gov/Public-Safety/2020-Racial-Profiling-RP-dataset/c65h-gw3m/data_preview.
- . 2023c. “2020 Racial Profiling (RP) Guide.” City of Austin, Texas Open Data Portal. https://data.austintexas.gov/Public-Safety/2020-Racial-Profiling-RP-Guide/64yt-89ub/data_preview.
- Choudhury, Nusrat. 2018. “New Data Reveals Milwaukee Police Stops Are about Race and Ethnicity,” February. <https://www.aclu.org/news/criminal-law-reform/new-data-reveals-milwaukee-police-stops-are>.
- City of Austin, Texas. n.d.a. “About Us.” <https://data.austintexas.gov/stories/s/g7cx-4kmk>.
- . n.d.b. “Terms of Use for the City of Austin Open Data Portal.” <https://data.austintexas.gov/stories/s/ranj-cccq>.

- Curtin, Kevin. 2019. “APD Weed Arrests Decline, but Racial Disparities Remain,” September. <https://www.austinchronicle.com/news/2019-09-20/apd-weed-arrests-decline-but-racial-disparities-remain/>.
- DeSilver, Drew, Michael Lipka, and Dalia Fahmy. 2020. “10 Things We Know about Race and Policing in the u.s.” *Pew Research Center*, June. <https://www.pewresearch.org/short-reads/2020/06/03/10-things-we-know-about-race-and-policing-in-the-u-s/>.
- Dorsey, Dustin. 2024. “Data from CA Traffic Stops Shows ‘Pervasive Pattern’ of Racial Profiling, Report Says,” January. <https://abc7news.com/racial-profiling-ca-traffic-stops-black-people-hispanics/14275828/>.
- Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. <https://CRAN.R-project.org/package=janitor>.
- Goodrich, Ben, Jonah Gabry, Imad Ali, and Sam Brilleman. 2024. “Rstanarm: Bayesian Applied Regression Modeling via Stan.” <https://mc-stan.org/rstanarm/>.
- Hardman, Ray. 2019. “Conn. Racial Profiling Panel Considers Health Outcomes for People Stopped by Police,” November. <https://www.ctpublic.org/mental-health/2019-11-07/conn-racial-profiling-panel-considers-health-outcomes-for-people-stopped-by-police>.
- Hester, Jim, Florent Angly, Russ Hyde, Michael Chirico, Kun Ren, Alexander Rosenstock, and Indrajeet Patil. 2024. *Lintr: A ‘Linter’ for r Code*. <https://CRAN.R-project.org/package=lintr>.
- Müller, Kirill. 2020. *Here: A Simpler Way to Find Your Files*. <https://CRAN.R-project.org/package=here>.
- Nahhas, Ramzi W. 2024. “6.2 Interpretation of the Logistic Regression Coefficients.” *Introduction to Regression Methods for Public Health Using R*. <https://www.bookdown.org/rwnahhas/RMPH/blr-interp.html>.
- Natarajan, Ranjana. 2014. “Racial Profiling Has Destroyed Public Trust in Police. Cops Are Exploiting Our Weak Laws Against It.” December. <https://www.washingtonpost.com/posteverything/wp/2014/12/15/racial-profiling-has-destroyed-public-trust-in-police-cops-are-exploiting-our-weak-laws-against-it/>.
- Oxford Learner’s Dictionaries. n.d. “Racial Profiling.” https://www.oxfordlearnersdictionaries.com/definition/american_english/racial-profiling.
- Poston, Ben, and Cindy Chang. 2019. “LAPD Searches Blacks and Latinos More. But They’re Less Likely to Have Contraband Than Whites,” October. <https://www.latimes.com/local/lanow/la-me-lapd-searches-20190605-story.html>.
- “Public Information Office.” n.d. <https://www.austintexas.gov/apd/media>.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoş Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *Arrow: Integration to ‘Apache’ ‘Arrow’*. <https://CRAN.R-project.org/package=arrow>.
- “The University of Texas System.” n.d. <https://www.utsystem.edu/>.
- Toronto Police Services. 2022. “Police Race and Identity Based Data - Use of Force.” City of Toronto. <https://open.toronto.ca/dataset/police-race-and-identity-based-data-use-of>

force/.

Valencia, Lila. 2021. “2020 Census Findings for Austin.” City of Austin Housing & Planning. <https://services.austintexas.gov/edims/document.cfm?id=368325>.

Waller, Allyson. 2018. “UT System’s 2017 Racial Profiling Report Sheds Light on Motor-Vehicle Contact Based on Race,” February. <https://thedailytexan.com/2018/02/21/ut-systems-2017-racial-profiling-report-sheds-light-on-motor-vehicle-contact-based-on/>.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Golemund, et al. 2019. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.