Mixed-Method Research Project and Racial Disparities Analysis Findings Report

Coalition of Homeless Service Providers
Monterey & San Benito Counties
Continuum of Care (CA-506)

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Acknowledgments

This research project was conducted by Miles Burgin (Quantitative Data Analyst) and Madeleine Smith (Qualitative Data Analyst and Researcher).

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Your insights and thoughtfulness were invaluable.

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Acronyms

a. BIPOC - Black, Indigenous, Person of Color
b. CHSP - Coalition of Homeless Service Providers
c. CoC - Continuum of Care
d. CoC CA-506 - CA Continuum of Care 506 (Monterey and San Benito Counties)
e. HDIS - Homeless Data Integration System
f. HMIS - Homeless Management Information System
g. HUD - United States Department of Housing and Urban Development
h. KII - Key Informant Interview
i. LEOH - Person with a lived experience of homelessness
j. NSD - No significant difference
k. RDA - Racial disparities analysis
l. TAY - Transition-aged Youth

Executive Summary

This report details a mixed-methods research project on racial disparity analyses conducted throughout the homeless service provision industry, known as the Continuum of Care (CoC), in the State of California. The research strategy behind this project relied on the statistical analysis of the Coalition of Homeless Service Providers Homeless Management Information System (HMIS) data from July 2020 through June 2021 as well as literature reviews and key informant interviews.

This research project was based on two main research questions and corresponding sub-questions. The key findings in this section are organized by those research questions, which are:

Table 1: Project-Wide Research Questions & Sub-questions	
Research Question	**Sub-Questions**
1. Are there racial disparities among the individuals who engage with the CHSPs system? If so, what are they?	**1a)** Are there racial disparities in access to CHSP programming? If so, who is experiencing less frequent access? Why? **1b)** Are there disparities within the homeless population that engages with CHSP systems? If so, who is engaging at disproportionately high rates? Disproportionately low rates? **1c)** Are there disparities in the outcome of individuals engaging with CHSP systems? If so, what are they?
2. What are some of the best practices for running racial disparity analyses in homeless populations?	**2a)** Are they conducting racial disparity analyses within their lead agencies? If so, how? **2b)** What are they doing with their findings? **2c)** What are their best practices? Challenges? Successes? Lessons learned?

Table 1: Project Research Questions & Subquestions

After researching appropriate datasets and running strategically chosen statistical analyses[1], it was found that there are large disparities in who experiences homelessness and engages with CoC CA-506, but once they engage those disparities reverse and communities of color achieve better outcomes than white individuals. Transition-aged youth perform particularly poorly with regard to their housing outcomes.

There are large disparities in who experiences homelessness and engages with CoC CA-506, but once they engage, those disparities reverse, and communities of color achieve better outcomes than white individuals. Transition-aged youth perform particularly poorly with regard to their housing outcomes.

When compared to their share of the regional[2] population, many races and ethnicities were either over or underrepresented. Statistical analyses showed that **American Indian and Native Alaskan, Black and African American, and Hispanic** individuals engaged with the Coalition of Homeless Service Providers programs at higher percentage rates than their share of the regional population. **Asian and White** individuals engaged at lower rates, and **Multiracial, Pacific Islander, and Native Hawaiian** individuals had no significant difference between their representation in the regional population and their engagement levels with the Coalition of Homeless Service Providers. Please see the table below for individual comparisons:

Table 2: Comparing Racial Representation CoC CA-506 System to overall County Population	
Race / Ethnicity	**Comparison**
American Indian and Native Alaskan	**7.8x more representation**
Asian	5.4x less representation
Black / African American	**2.8x more representation**
Pacific Islander and Native Hawaiian	No significant difference (NSD)
Multiracial	No significant difference (NSD)
White	1.2x less representation

[1] Can be found in Appendix 1 (Methodology)
[2] Defined as Monterey and San Benito Counties

Hispanic	**1.07x more representation**

Table 2: Comparison Between Racial Share of Regional Population and CoC CA-506

Further tests were run to determine the presence of racial disparities in the length of engagement with CHSP and the housing outcomes (where individuals go upon exiting the CoC's system). Each racial and ethnic group was compared to non-Hispanic, non-Transition-aged youth (TAY) white individuals to highlight any disparities. The findings from these tests highlighted that **Multiracial** individuals were twice as likely to be placed in temporary housing; **Black and African American** individuals are about half as less likely to return to homelessness and one and half times as likely to be placed in permanent housing; **Pacific Islander and Native Hawaiian** individuals were 3.83 times less likely to return to homelessness, and 2.7 times more likely to be placed in permanent housing; **Hispanic** individuals were 27% (0.73 times) less likely to return to homelessness and 1.6 times more likely to be placed in temporary housing; and **transition-aged youth individuals** were two times as likely to return to homelessness and 49% percent less likely to be placed in permanent housing. This information can be summarized in the data table below.

Table 3: Destination Category likelihoods when compared to non-Latino, non-TAY Whites

Identity	Return to Homelessness	Permanent	Temporary	Institutional	Other
Multiracial	-	-	197.75%	-	-
American Indian	-	-	-	-	-
Asian	-	-	-	-	-
African American	56.29%	154.24%	-	-	-
Pacific Islander	26.08%	272.08%	-	-	-
Latino	73.06%	-	159.23%	-	-
TAY	196.66%	51.30%	-	-	-
Predictiveness	56.79%	55.76%	55.83%	57.99%	55.94%

Table 3: Destination Category Likelihoods When Compared to non-Latino, non-TAY Whites

Each racial subpopulation was also **compared to other racial and ethnic identities** to see if any disparities existed among different minority groups. The findings of these tests concluded that no significant disparities existed for Multiracial, American Indian and Native Alaskan, Asian, or Pacific Islander and Native Hawaiian individuals. That being said, **White** individuals were 1.4 times more likely to return to homelessness, 19%

less likely to be placed in permanent housing, and 37% less likely to be placed in temporary housing. **Hispanic** individuals were 16% less likely to return to homelessness and 1.3 times more likely to end up in temporary housing. Finally, **Transition-aged Youths** were still 2 times more likely to return to homelessness and 49% less likely to be placed in permanent housing.

Qualitative research also found that the environment around racial disparity analyses varies depending on Continuums of Care (CoC) demographic breakdown, geography, and size. While every CoC interviewed saw the value of running racial disparity analyses, for some, it's either not a priority or not an option. Of the 44 CoC regions in the State of California, six[3] participated in a key informant interview for this project. They were 1) Butte County, 2) Kern County, 3) Lake County, 4) Pasadena, 5) Santa Clara, and 6) Santa Cruz. Deep learnings were also pulled from Oakland-Berkeley-Alameda County's *Centering Racial Equity in Homeless System Design*, published in January 2021 and California's Homeless Data Integration System (HDIS) website.

Key informants provided invaluable insight into their challenges, successes, and best practices for running racial disparity analyses and implementing programmatic and behavior change within their organizations. Some **high-level challenges** revolved around securing decision-maker buy-in, effective outreach, and CoC capacity (whether financial or staff-related). **Major successes** typically included the establishment of some kind of governing body (a committee, advisory board, task force, etc.) devoted to this subject matter, or some kind of organizational policy change and implementation (incorporating custom data metrics into new partner contracts, hiring a diverse group of Board members, etc.).

Each CoC interviewed had a handful of innovative practices that they deemed as "best", or essential, to the success of their organization's mission. These practices fell into several categories: 1) data practices, 2) policy and procedural recommendations, 3) staffing practices, 4) funding criteria, 5) outreach strategies, 6) programming recommendations, 7) advocacy work, and 8) fostering more community partnerships. Details on these practices can be found in the Key Findings section of this report. This research project also highlighted that other CoCs are thinking similarly to CHSP about their approach to finding racial disparities by using metrics like entry, exit, and destination data to run statistical tests.

Final recommendations for CoC CA-506 fall into six main categories, which are outlined in the table below:

[3] Not a statistically significant nor representative sample of CA CoCs

Table 4: Recommendations	
Data	● Expand statistical analysis of racial disparities ● Make culturally inclusive data collection tools ● Hire racially representative data collection teams
Policies, Procedures, and Programming	● Build out frameworks and develop policies through a cultural, ethnic, and racial lens
Staffing	● Hire racially and culturally diverse people at every level of the decision-making process
Funding	● Find funding opportunities for specific racial and ethnic subgroups
Outreach	● Develop a strong Outreach Strategy ● Invest in field teams of varying degrees to conduct outreach through a physical and mental health lens
Advocacy	● Foster continual community conversations - be a thought leader! ● Research and address external systems of racial oppression and advocate for policies that dismantle them

Table 4: Recommendations

Introduction

The Coalition of Homeless Service Providers (CHSP) decided to invest in a research project on best practices for running an annual racial disparities analysis (RDA) on the homeless population throughout other CoCs in the State of California. One of the goals of this research was to build out a process for CoC CA-506 to conduct RDA's on an annual basis, in hopes of improving service outcomes and expanding federal grant eligibility for the organization. The objectives of this project included running statistical tests on CoC CA-506's Homeless Management Information System (HMIS) data to illuminate the rates of engagement by race and ethnicity, analyzing any disparities that may be found, as well as conducting comprehensive research on other CoC's throughout the State of California and key informant interviews with experts.

Limitations

The Data

The nature of data on homeless populations, in general, comes as a limitation due to the hidden nature of homeless populations. Datasets used for this analysis (HMIS, ACS) only encapsulate individuals who engage with the systems responsible for gathering data and reporting it out.

Key Informant Sampling

The key informant interview (KII) sampling was roster-based but was subject to a self-selection bias. The final number of interviews conducted is not a representative sample of the CoC population in the State of California. On top of this, a semi-structured interview protocol was used; informants were asked similar, but potentially different, questions based on their unique circumstances.

Methodology

This was a mixed-method research project, utilizing both a quantitative statistical analysis of homeless populations in Monterey and San Benito Counties, as well as a qualitative research approach consisting of a literature review and key informant interviews to inform the findings and recommendations provided in this report. More information on this can be found in the Appendices.

Background

The Coalition of Homeless Service Providers (CHSP) is the Lead Agency of CoC CA-506, which contains Monterey and San Benito counties. CHSP manages a coalition of local homeless service providers with a mission to eliminate homelessness in Monterey and San Benito Counties by promoting regional partnerships and interagency collaboration for a comprehensive system of housing. While CHSP does not explicitly provide services to individuals experiencing homelessness, they are the administrative body managing the network-wide coordinated entry system and all of the Homeless Management Integration System (HMIS) data that they collect. CHSP ran it's first racial disparities analysis in 2018, but has not conducted any others until now.

A racial disparities analysis (RDA) is a statistical analysis identifying racial disparities in terms of access, outcomes or other indicators within the CoC. Racial disparity analyses are the new normal for adequate service provision and policy advocacy across the nation. The existence of racial disparities within HMIS data can imply inequities in CoC CA-506's overall system, which can lead to unequal outcomes in housing provision. This is, ultimately, not in alignment with CHSP's mission.

CHSP chose to spearhead this initiative and contracted graduate level students from the Middlebury Institute of International Studies to help them conduct this analysis with the hopes that it would improve service provision through its network and open up more federal grant opportunities.

Key Findings

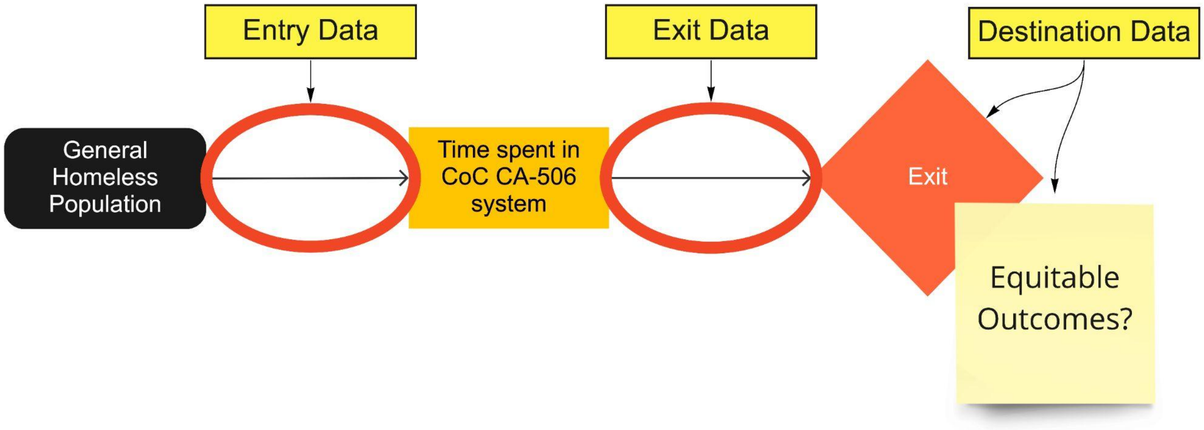
Major key findings from this research project were based on two main research questions and corresponding sub-research questions. The key findings in this section will be organized by those research questions, which can be found in the table below.

Table 5: Research Questions & Sub-Questions	
1. Are there racial disparities among the individuals who engage with the CoC CA-506 system? If so, what are they?	1a) Are there racial disparities in access to CoC CA-506 systems? If so, who is experiencing less frequent access? Why? 1b) Are there disparities within the homeless population that engages with CoC CA-506 systems? If so, who is engaging at disproportionately high rates? Disproportionately low rates? 1c) Are there disparities in the outcome of individuals engaging with CoC CA-506 systems? If so, what are they?
2. What are some of the best practices for running racial disparity analyses?	2a) Are other CoC's currently conducting racial disparity analyses with their lead agencies? If so, how? 2b) What are they doing with their findings? 2c) What are there best practices? Challenges?

Table 5: Research Questions & Sub-Questions

Key Finding 1 - There are large disparities in who experiences homelessness and engages with CoC CA-506, but once they engage, those disparities reverse and communities of color achieve better outcomes than white individuals. *(Research Question #1a-c)*

The statistical analyses ran for this study focused on three potential points in the process where racial disparities could occur; access and/or entry into the system, experience within the system, and where individuals go upon exiting the system (housing outcomes).



Graphic 1 - Flow chart of areas of interest

The statistical analyses portion of this project had its own set of research questions and sub-questions, which are outlined in the table below.

Table 6 - Statistical Analysis Research Questions & Sub-Questions	
1. Is CoC CA-506's system serving people of different races at disproportionate rates?	1a) Is someone's race predictive of their likelihood to engage with CoC CA-506?
2. Do the young people we serve engage with CoC Project types (or Organizations) at disproportionate rates?	2a) Is being a transition-aged youth (18-24) predictive of someone's likelihood of engaging with CoC CA-506?
3. Do racial subpopulations achieve various housing outcomes at disproportionate rates or speeds as a result of engaging with CHSP?	3a) Is someone's race predictive of their housing outcomes after engaging with CoC CA-506? 3b) Is being a transition-aged youth (18-24) predictive of their housing outcomes after engaging with CoC CA-506?

Table 6 - Statistical Analysis Research Questions & Subquestions

Engagement with the Continuum of Care System *(Statistical Analysis Research Question #1-1a)*

Tests showed varying levels of representation within the CHSP system depending on the race or ethnicity in question. While **American Indian and Native Alaskan** individuals make up less than 0.2% of the regional population, they represent 1.32% of the individuals engaging with CHSPs programs[4]. This is a statistically significant[5] overrepresentation; 7.8 times their regional population share. **Asian** individuals also showed a significant difference between the CHSP sample population and the regional population. While they make up 5.2% of the Monterey and San Benito counties population, they only make up 0.97% of individuals engaging with the CHSP system, making them underrepresented by about 5.4 times. **Black and African American** individuals are overrepresented in the CHSP system by about 2.8 times their regional population share; while they make up 2.2% of Monterey and San Benito counties, they make up 6.8% of the individuals engaging with CHSP's system. **Pacific Island and Native Hawaiian** individuals did not show any significant difference in their rates of engagement with CHSP in comparison with their share of the regional population. **White** individuals were underrepresented in the CHSP system by 1.2 times, meaning that while they make up 51% of the Monterey and San Benito County populations, they only make up 24.3% of the individuals who engage in the CHSPs system. **Multiracial** individuals[6] engaged with CHSPs system at an expected rate, given their make up of the regional population. And finally, Hispanic individuals were overrepresented in CHSPs system by roughly 7%, although this finding did have statistical significance. Please refer to the table below for a visual guide to this information.

Table 1: Demographic Differences in Engagement with Services

Group Name	% of Monterey and San Benito Counties	Low	Actual	High	p-value
American Indian and Alaska Native	0.17%	0.94%	**1.32%**	1.70%	<0.0001
Asian	5.21%	0.65%	**0.97%**	1.30%	<0.0001
Black/African American	2.22%	5.36%	**6.16%**	6.96%	<0.0001
Pacific Islander/Native Hawaiian	0.38%	0.37%	**0.63%**	0.89%	0.06188
White	30.02%	22.87%	**24.29%**	25.71%	<0.0001
Multiracial	2.75%	2.26%	**2.81%**	3.36%	0.8379
Latino	59.25%	62.22%	**63.82%**	65.42%	<0.0001

Table 7 - Racial Subpopulation Rate of Engagement with CoC CA-506 Compared to the Regional Population

[4] Used interchangeably with "system" throughout this report
[5] Tested at a 95% confidence interval with a p-value of less than 0.05.
[6] Defined in this study as any individual claiming two or more races, not including hispanic ethnicity.

Experience within the CoC CA-506 System (Length of Engagement)
The analysis also examined the length of time that individuals engaged with homeless services. Overall, identity is a poor predictor of length of engagement, while the destination code to which someone exited services was a fairly good predictor. Once controlling for exit destination, only **Pacific Islanders and Native Hawaiians** showed any statistically significant difference in engagement length and were expected to be enrolled in services for 116 days longer than non-Latino, non-Transition Aged Whites.

Experience upon Exiting the CoC CA-506 System (Housing Outcomes) ***(Statistical Analysis Research Question #3-3a)***
While significant disparities exist in regard to who becomes homeless and engages with services in Monterey and San Benito Counties, once individuals engage with services, those disparities reverse, and **people of color are more likely to obtain positive housing outcomes** after engagement than their white counterparts. Meanwhile, **Transition-Aged Youth** achieve very poor housing outcomes when compared to other age groups. Please see the table below for quantitative findings.

Table 3: Destination Category likelihoods when compared to non-Latino, non-TAY Whites

Identity	Return to Homelessness	Permanent	Temporary	Institutional	Other
Multiracial	-	-	197.75%	-	-
American Indian	-	-	-	-	-
Asian	-	-	-	-	-
African American	56.29%	154.24%	-	-	-
Pacific Islander	26.08%	272.08%	-	-	-
Latino	73.06%	-	159.23%	-	-
TAY	196.66%	51.30%	-	-	-
Predictiveness	56.79%	55.76%	55.83%	57.99%	55.94%

Table 8: Destination Category likelihoods when compared to non-Latino, non-TAY Whites

Key Finding 2 - Best practices for running racial disparity analyses vary by region. *(Research Question #2)*
Many CoCs included in this research project have developed deeply comprehensive and innovative ways to conduct racial disparity analyses more efficiently over time, resulting in deeper impact. Some of the best practices include actions like 1) involving individuals with lived experience of homelessness (LEOH) at every step of program

design and implementation (whether that be in an advisory or paid role), 2) evaluating how you approach your data categorization and analysis, and 3) developing intercultural competency and/or racial equity frameworks that inform policy and process development (focusing heavily on outreach).

Involving Individuals with Lived Experience of Homelessness

A common thread among all CoCs interviewed and researched was that including people with lived experience of homelessness was imperative to the success of their program approach. Multiple key informants spoke adamantly, in one way or another, about including these individuals in conversations about program design and program implementation. A few experts talked about developing advisory boards populated by individuals with lived experience of homelessness, as they are experts on the services being provided. Individuals with lived experience of homeless also serve as incredible thought partners for program innovation, and help agencies identify service provision gaps. This type of representation is incredibly meaningful to the populations CoCs are serving, as it can build trust across cultural, and even linguistic, boundaries. One stakeholder elaborated, stating that having Black, Indigenous, and Persons of Color (BIPOC) individuals with lived experiences of homelessness on decision-making bodies can help guide decision-making from the beginning, which increases the efficacy and efficiency of the programs implemented. Another stakeholder spoke passionately about the need to not only include BIPOC individuals with lived experiences of homelessness at multiple levels of the programming process but to actually hire and compensate them for their time.

Data Categorization and Analysis

Many key informants spoke to the importance of equitable data methodology, processes, and management in the effort to reduce racial disparities. When it comes to methodology, at least half of informants spoke to the inadequacy of the United States Department of Housing and Urban Development's (HUD) race and ethnicity breakdown and definitions. Informants from multiple areas talked at length about how their teams have invested time in creating locally meaningful metrics that represent their communities. In addition to this, informants spoke to the importance of finding ways to overlap or integrate the race and ethnicity variables, as they are not entirely separate in real life. This comes into play when speaking to the Multiracial race variable and the Hispanic ethnicity variable. Informants also noted that data analysis should be expanded outside the scope of the Continuum of Care. Informants in Southern California discussed how they compare there racial disparities findings with that of other local institutions, such as jails or prisons.

As for data collection, reviewing data collection tool development through a racial equity lens is an important step in ensuring that data collection is equitable both in the information it is gathering and in the way it is distributed. A few other best practices included scheduling monthly meetings to review key performance indicators' progress and relevance, building new metrics into partner contracts, and including the data teams in strategic planning meetings so that changes made can be implemented at all levels.

As for overarching approach to racial disparity analyses, at least half of those interviewed did not run a statistical racial disparities analysis regularly. Many CoC's are currently running them on an "as needed" basis. However, others did run racial disparity analyses regularly, and they had well thought out approaches. An example of this would be the Pasadena CoC. They first implemented their annual analysis in 2018 at a relatively high level (comparing the homeless population to the city's general population and the city population living below the poverty line), and then began reviewing different program types and looking at enrollments broken down by race, ethnicity, and outcomes. The goal of this shift in analysis approach was to see if they were exacerbating any disparities with their service provision.

Developing Intercultural Competency and/or Racial Equity Frameworks that Inform Policy and Process Development

A handful of key informants interviewed had already developed highly detailed intercultural competency criteria or a racial equity framework that they applied throughout their service provision. One example is the Racial Equity Impact Analysis framework used throughout the Oakland-Alameda-Berkeley CoC, which is a "data-driven, structured problem-solving approach that explores the systemic benefits and burdens on communities most impacted by racial disparities when designing and vetting potential solutions to ending and preventing homelessness"[7]. Another example would be the Kern County CoC Cultural Competence Plan, which has detailed structure and strategically outlined criteria, goals, and strategy to combat racial inequities through cultural competence. Both of these frameworks rely heavily on an intersectional focus that relies on inclusion of marginalized communities and innovative means to create solutions.

Key Finding 3 - Some of the biggest challenges in prioritizing racial disparity analyses seem to be decision-maker or community buy-in, CoC lead agency capacity, and consistently effective outreach. *(Research Question #2d)*

Challenges experienced by other CoCs throughout the State of California came most often from things outside of CoC control. The overarching challenges that most key

[7] *Centering Racial Equity in Homeless System Design*, Oakland-Alameda-Berkeley CoC, January 2021

shared fell into one of three buckets: 1) decision-maker or community buy-in, 2) CoC lead agency capacity, and 3) Consistently effective outreach.

Decision-Maker or Community Buy-In
One of the largest challenges for CoCs can be securing support from decision-making bodies (such as local City Councils, or governmental offices). This can come from a lack of diversity within decision-making bodies, a lack of understanding, or a lack of resources (either financial or human). One stakeholder attributed some of this resistance to the high level of turnover within their county's administration. Claiming to be a "small, poor" county with a major housing shortage, it is difficult for them to keep county employees locally. Due to this high level of turnover, their county administrators are just now beginning to see the high demand for affordable housing.

Despite resistance from conservative decision-makers in some areas, movement is beginning to happen. According to a handful of stakeholders interviewed, top-down influence from HUD's new requirements for demographics has influenced some movement from these stagnant areas.

CoC Lead Agency Capacity
CoCs vary in size, and therefore funding, throughout the State of California. A couple of informants that participated in this research project were on the smaller side, and one of them was self-described as a "very poor" county, with minimal funding sources. These resource shortcomings have caused them to put racially equitable programming on hold. One informant shared that after nearly three years of conversations, their CoC has just established their first Equity Committee. Another informant shared that while they knew that this kind of analysis was important, they couldn't spare the staff to run it based on the low number of BIPOC individuals they saw utilizing their services.

Effective and thorough outreach is inherently difficult
Each informant interviewed spoke at length about how effective outreach was a hard thing to maintain. Building trust with homeless individuals is difficult, and this impacts penetration rates throughout many regions. There are many contributing factors to this reality: language barriers, nomadic populations, lack of trust in service providers, and more.

Key Finding 4 - Most of the CoCs that are currently conducting racial disparity analyses are using their findings for policy or programming revisions. *(Research Question #2c)*
CoCs that are running racial disparity analyses on a regular basis are using their findings to implement changes in their policies and service provision. Many are already including people with lived experience of homelessness in their advisory bodies,

building out policies that require these invaluable stakeholders to be present at all stages of brainstorming or strategic planning. Many are already utilizing racial equity frameworks, whether formal or informal. Many are being critical with the way they are categorizing, collecting and quantifying data. And many are using their findings to refine their outreach efforts. Some CoCs are using these statistical analyses to build entire initiatives for specific subpopulations or specific obstacles their participants may face. One major aspect of this is the cultural identities that exist underneath race and ethnicity. Kern County CoC has done an amazing job at building out their Cultural Competency Plan, which gets reviewed and updated consistently. Other are building out resourceful and collaborative housing programs, with a “Housing First” approach. Others are conducting Landlord Engagement and House Matching programs.

What’s very clear is that service providers are listening to people experiencing homelessness and trying their best to find innovative solutions to these difficult circumstances.

Recommendations

The recommendations developed from this research project have been organized in alignment with the themes captured from conversations around best practices that key informants shared. The overarching themes of the recommendations are 1) Data, 2) Policies, Procedures, and Programming, 3) Staffing, 4) Funding, 5) Outreach, and 6) Advocacy. Please see the table below for an overview.

Table 9: Recommendations	
Data	● Expand statistical analysis of racial disparities to ● Make culturally inclusive data collection tools ● Hire racially representative data collection teams
Policies, Procedures, and Programming	● Build out frameworks and develop policies through a cultural, ethnic, and racial lens
Staffing	● Hire racially and culturally diverse people at every level of the decision-making process
Funding	● Find funding opportunities for specific racial and ethnic subgroups
Outreach	● Develop a strong Outreach Strategy ● Invest in field teams of varying degrees to conduct outreach through a physical and mental health lens
Advocacy	● Foster continual community conversations - be a thought leader! ● Research and address external systems of racial oppression and advocate for policies that dismantle them

Table 9: Recommendations

Conclusion

The Coalition of Homeless Service Providers is on the right track to help CoC CA-506 spearhead racial equity efforts throughout the region. Already, CHSP has begun important first steps on the road to building a racially equitable environment in real time. Currently, CoC CA-506 is spearheading a Youth Homelessness Demonstration Program (YHDP) that will help bring more transition-aged youth into the conversation to help CHSP understand the tumultuous nature of their experience within CoC CA-506 system and build accessible programs to address it. On top of that, staff at CHSP are in the midst of developing an equity framework, pulling from resources mentioned in this report like the Racial Equity Impact Analysis Framework. Investments have already been made into building an outreach team that can meet homeless individuals where they are instead of expecting them to come find services. And CHSP has also already begun strategizing how to hire persons with lived experience of homelessness onto the team.

These kinds of actions, and more, will hopefully lead to closing some of the gaps seen in the statistical analysis findings; or at least highlight further complexities that can then be addressed.

Appendices

Limitations

The Data

The nature of data on homeless populations, in general, comes as a limitation due to the hidden nature of homeless populations. Datasets used for this analysis (HMIS, ACS, PIT) only encapsulate individuals who engage with the systems responsible for gathering data and reporting it out.

Key Informant Sampling

The KII sampling was roster-based but was subject to a self-selection bias. The final number of interviews conducted is not a representative sample of the CoC population in the State of California. On top of this, a semi-structured interview protocol was used; informants were asked similar, but potentially different, questions based on their unique circumstances.

Methodology

This was a mixed-method research project, utilizing both a quantitative statistical analysis of homeless populations in Monterey and San Benito Counties, as well as a qualitative research approach consisting of a literature review and key informant interviews to inform the findings and recommendations provided in this report.

Tool	Detail
Research Design Matrix	An organizational tool used to identify and outline the main research questions, sub-questions, and logistical information on processes for conducting the research.
Literature Review	The literature review consisted of finding sources on best practices for conducting RDAs and finding annual reports from CoC about running these tests.
Key Informant Interviews	Knowing that some CoCs were prioritizing RDAs more than others, key informants were chosen for deeper research. A semi-structured Key Informant Interview (KII) Protocol was developed.
Statistical Testing Using R (including R script)	Used to find racial disparities in the Coordinated Entry Program data.

Research Design Matrix

The Research Design Matrix for this project can be found here.

Key Informant Interviews
Key informant interviews were utilized to create some context for the quantitative data found in the literature review. Out of the 44 Continuums of Care contacted, 6 CoCs responded and agreed to voluntarily participate. Those informants were:

- Butte County (CA-519)
- Lake County (CA-529)
- Kern County (CA-604)
- City of Pasadena (CA-607)
- Santa Clara County (CA-500)
- Santa Cruz County (CA-508)

Here is a visual representation of where these informants are located throughout the State of California:

A semi-structured interview protocol, focused on racial disparities analysis processes and best practices, was developed. The protocol can be found below:

Key Informant Interview Questions - March 2022

Zoom call-in info:

Hello! My name is [Name] and I am an [role] at (Organization]. I am working with the Coalition of Homeless Service Providers to conduct a comprehensive landscape analysis around best practices for conducting racial disparities analyses. The goal is to better understand how statewide CoCs conduct their racial disparities analyses, how it informs their service provision and strategy, and how it impacts their community. Today, I'd like to have a conversation about your work within your CoC region. Throughout the conversation, please your responses will be kept confidential so your answers are candid. That is, we will not be tying any of your comments to your name in our analysis. Please also feel free to relax and answer honestly and organically - I'm here to learn about your experience and I hope this will be a productive conversation! This interview shouldn't take more than 30 minutes.

Alright, shall we begin?

Is it alright with you if I record this session? The recording is only for our note-taking purposes and we will not share it with anyone else and we will delete it once the evaluation is complete.

[Press record]

Excellent.

[Notes: The interviews will be conducted in a semi-structured manner, meaning questions will be selected as they are relevant to informants. Informants will be asked a sample of these questions, but not all of them. Additional questions may be added, based on the informant's individual responses to the survey.]

1. Can you tell me a little bit about your organization and your role within it?
2. Are you currently conducting racial disparities analyses? If so, how? How often? If not, why?
3. How are you shaping your conversations around racial disparities?
4. Do your analyses result in any policy changes? If so, how? If not, why?
5. What are your best practices for running racial disparities analyses?
6. **What are your challenges, successes, and lessons learned?**
7. Do your racial disparities findings impact your service provision strategy or approach? If so, how? If not, why?
8. What level of priority are racial disparities to your organization?

Statistical Testing using R

Statistical analysis began with intensive data manipulation. First, individuals who had missing or
incomplete demographic information were removed from the dataset. Next, variables were created in order to separate multiracial individuals from those with only one racial identity. Similar separation was conducted to parse Latino from non-Latino individuals. Following this separation, new variables were created for each of the five HUD

recognized racial identities and included individuals with only that racial identity. Next, each individual's age on the date they enrolled in services was calculated in order to identify Transition Aged Youth, and finally, exit destinations were categorized according to guidance provided by CHSP.

Statistical analysis consisted of three sets of tests. First, single sample t-tests were utilized in order to identify if various demographic groups engaged with services at rates different from their share of the population. For each racial and ethnic identity analyzed, these t-tests compared the percentage of all individuals enrolled in services with CHSP as seen in the HMIS database against the percentage of the overall population in Monterey and San Benito Counties composed of individuals of that racial or ethnic identity.

Second, logistical regressions were used to identify any disparities among demographic groups in the living situations in which they exited services. These regressions were compared against two different populations – first comparisons were made against non-Latino, non-TAY whites, and second, comparisons were made against anyone of a different racial/ethnic/or age group. For comparisons against non-Latino, non-TAY whites, five models were analyzed - one for each destination category - and were structured as follows:

[Destination Category] ~ Multiracial + American Indian + Asian + Black + Pacific Islander + Latino + TAY

For comparisons against every one of a different racial/ethnic/TAY identity, forty separate models were created – one for each combination of exit destination and identity – and were structured as follows:

[Destination Category] ~ [Identity]

Finally, multiple regressions were used to determine if there were disparate lengths of engagement with services (measured in days) among the racial, ethnic, and TAY identities analyzed. Three models were utilized in this analysis. The first model looked only at race, ethnicity, and TAY status, and was structured as follows:

Length of Engagement ~ Race + Ethnicity + TAY

The second model accounted for the destination category to which the client exited services and was structured as follows:

Length of Engagement ~ Race + Ethnicity + TAY + Destination Category

The final model was similar to the previous model, except analyzed individual HUD defined destination codes instead of the categories created by CHSP. The model was structured as follows:

Length of Engagement ~ Race + Ethnicity + TAY + Destination Code

R Script

```
### SETUP ###
# Install Necessary Packages
#install.packages("ggpubr", dependencies = TRUE) #install.packages("dplyr",
dependencies = TRUE) #install.packages("lubridate", dependencies = TRUE)
#install.packages("ROCit", dependencies = TRUE)
# Open Necessary Packages library(ggpubr) library(dplyr) library(lubridate)
library(ROCit)
#Import Data
episodes <- read.csv("episodes.csv") #the name of the .csv should be the same as the
output in grant's script
##Remove Rows w '99', '9', or '8' entries - This is done to ensure that everyone in the
list has a racial/ethnic identity assigned. Without this step the T.Tests will not function
properly
episodes1 <- episodes[!(episodes$AmIndAKNative == 99 | episodes$Asian == 99 |
episodes$BlackAfAmerican == 99 |
episodes$NativeHIPacific == 99 | episodes$White == 99 | episodes$Ethnicity == 99 |
episodes$Ethnicity == 9 |episodes$Ethnicity == 8 | episodes$AmIndAKNative == 0 &
episodes$Asian == 0 & episodes$BlackAfAmerican == 0 &
episodes$NativeHIPacific == 0 & episodes$White == 0),]
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## Create Necessary Variables ##
# Create Multiracial Variable # An individual is multiracial if they 1) have two or more
racial identities, and 2) if they are NOT latino.
clientCleanMR <- episodes1%>%
mutate(Multiracial = case_when(AmIndAKNative == 1 & Asian == 1 & Ethnicity == 0 ~
1,
AmIndAKNative == 1 & BlackAfAmerican == 1 & Ethnicity == 0 ~ 1, AmIndAKNative ==
1 & NativeHIPacific == 1 & Ethnicity == 0 ~ 1, AmIndAKNative == 1 & White == 1 &
Ethnicity == 0 ~ 1,
Asian == 1 & BlackAfAmerican == 1 & Ethnicity == 0 ~ 1,
Asian == 1 & NativeHIPacific == 1 & Ethnicity == 0 ~ 1,
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Asian == 1 & White == 1 & Ethnicity == 0 ~ 1,
BlackAfAmerican == 1 & NativeHIPacific == 1 & Ethnicity == 0 ~ 1,
BlackAfAmerican == 1 & White == 1 & Ethnicity == 0 ~ 1,
NativeHIPacific == 1 & White == 1 & Ethnicity == 0 ~ 1,
AmIndAKNative == 1 & Asian == 0 & BlackAfAmerican == 0 & NativeHIPacific == 0 &
White == 0 & Ethnicity == 0 ~ 0,
AmIndAKNative == 0 & Asian == 1 & BlackAfAmerican == 0 & NativeHIPacific == 0 &
White == 0 & Ethnicity == 0 ~ 0,
AmIndAKNative == 0 & Asian == 0 & BlackAfAmerican == 1 & NativeHIPacific == 0 &
White == 0 & Ethnicity == 0 ~ 0,
AmIndAKNative == 0 & Asian == 0 & BlackAfAmerican == 0 & NativeHIPacific == 1 &
White == 0 & Ethnicity == 0 ~ 0,
AmIndAKNative == 0 & Asian == 0 & BlackAfAmerican == 0 & NativeHIPacific == 0 &
White == 1 & Ethnicity == 0 ~ 0,
Ethnicity == 1 ~ 0))
### Separate mono racial from multiracial individuals An individual is monoracial if they
are not multiracial or latino.
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# Create AmIndOnly Variable clientCleanMR <- clientCleanMR%>%
mutate(AmIndOnly = case_when(AmIndAKNative == 1 & Multiracial == 0 & Ethnicity ==
0 ~ 1, AmIndAKNative == 0 ~ 0,
Multiracial == 1 ~ 0,
Ethnicity == 1 ~ 0)) clientCleanMR$AmIndOnly
#Create AsianOnly Variable clientCleanMR <- clientCleanMR%>%
mutate(AsianOnly = case_when(Asian == 1 & Multiracial == 0 & Ethnicity == 0 ~ 1,
Asian == 0 ~ 0,
Multiracial == 1 ~ 0,
Ethnicity == 1 ~ 0)) clientCleanMR$AsianOnly
# Create BlackOnly Variable clientCleanMR <- clientCleanMR%>%
mutate(BlackOnly = case_when(BlackAfAmerican == 1 & Multiracial == 0 & Ethnicity ==
0 ~ 1, BlackAfAmerican == 0 ~ 0,
Multiracial == 1 ~ 0,
Ethnicity == 1 ~ 0)) clientCleanMR$BlackOnly
#Create PIOnly Variable clientCleanMR <- clientCleanMR%>%
mutate(PIOnly = case_when(NativeHIPacific == 1 & Multiracial == 0 & Ethnicity == 0 ~
1, NativeHIPacific == 0 ~ 0,
Multiracial == 1 ~ 0,
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Ethnicity == 1 ~ 0)) clientCleanMR$PIOnly
#Create WhiteOnly Variable clientCleanMR <- clientCleanMR%>%
mutate(WhiteOnly = case_when(White == 1 & Multiracial == 0 & Ethnicity == 0 ~ 1,
White == 0 ~ 0,
Multiracial == 1 ~ 0,
Ethnicity == 1 ~ 0)) clientCleanMR$WhiteOnly
#convert DOB field to date
clientCleanMR$DOB <- as.Date(clientCleanMR$DOB, "%m/%d/%Y")
clientCleanMR$DOB
#create age variable - Age is calculated on the day that the client was entered into
HMIS
clientCleanMR$Age =
floor(as.numeric(difftime(clientCleanMR$EntryDate,clientCleanMR$DOB, units =
"weeks"))/52.5)
clientCleanMR$Age
#create TAY variable An individual is considered TAY if they are between 18 and 24,
and are either the Head of Household or spouse/partner of the HoH
clientCleanMR <- clientCleanMR%>%
mutate(TAY = case_when(Age >= 18 & Age <= 25 & RelationshipToHoH ==1 ~ 1,
Age >= 18 & Age <= 25 & RelationshipToHoH ==3 ~ 1, Age <= 18 ~ 0,
Age >= 25 ~ 0,
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RelationshipToHoH ==2 ~0, RelationshipToHoH ==4 ~0, RelationshipToHoH ==5 ~0,
RelationshipToHoH ==99 ~0))
clientCleanMR$TAY
#Create coded destination variable - These destinations were coded according to
Grant's preferences. Any future changes to destination categories should be made here.
clientCleanMR <- clientCleanMR%>%
mutate(DestCoded = case_when(Destination == 22 ~ "Permanent",
Destination == 23 ~ "Permanent", Destination == 26 ~ "Permanent", Destination == 28 ~
"Permanent", Destination == 19 ~ "Permanent", Destination == 3 ~ "Permanent",
Destination == 31 ~ "Permanent", Destination == 33 ~ "Permanent", Destination == 34 ~
"Permanent", Destination == 10 ~ "Permanent", Destination == 20 ~ "Permanent",
Destination == 21 ~ "Permanent", Destination == 11 ~ "Permanent", Destination == 18 ~
"Temporary", Destination == 2 ~ "Temporary", Destination == 32 ~ "Temporary",
Destination == 13 ~ "Temporary", Destination == 36 ~ "Temporary", Destination == 12 ~
"Temporary", Destination == 35 ~ "Temporary",
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Destination == 27 ~ "Temporary",
Destination == 15 ~ "Institutional", Destination == 6 ~ "Institutional",
Destination == 7 ~ "Institutional",
Destination == 25 ~ "Institutional",
Destination == 4 ~ "Institutional",
Destination == 5 ~ "Institutional",
Destination == 16 ~ "Return to Homelessness", Destination == 1 ~ "Return to
Homelessness", Destination == 14 ~ "Return to Homelessness", Destination == 18 ~
"Return to Homelessness", Destination == 29 ~ "Other",
Destination == 30 ~ "Other", Destination == 17 ~ "Other", Destination == 24 ~ "Other",
Destination == 37 ~ "Other", Destination == 8 ~ "Other", Destination == 9 ~ "Other",
Destination == 99 ~ "Other"))
#Create Length of Episode of engagement with CHSP
clientCleanMR$Length =
as.numeric(difftime(clientCleanMR$ExitDate,clientCleanMR$EntryDate, units = "days"))
clientCleanMR$Length
#Remove Duplicate Rows
clientCleanMR <- clientCleanMR%>% distinct() clientCleanMR
```

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#Rename data for Multiple Regression (R Chooses its comparison group based on
alphabetical order. Adding "a_" in front of a category makes it our comparison group)
clientCleanMR1 <- clientCleanMR
clientCleanMR1 <- clientCleanMR1%>%
mutate(Race = case_when(Multiracial == 1 ~ "Multiracial",
AmIndOnly == 1 ~ "AmIndAKNative", AsianOnly == 1 ~ "Asian",
BlackOnly == 1 ~ "BlackAfAmerican", PIOnly == 1 ~ "NativeHIPacific", WhiteOnly == 1
~ "a_White", Ethnicity == 1 ~ "Latino"))
#clientCleanMR1 <- clientCleanMR1%>%
# mutate(Latino = case_when(Ethnicity == 1 ~ "Latino", # Ethnicity == 0 ~
"a_Non-Latino"))
clientCleanMR1 <- clientCleanMR1%>% mutate(TAY1 = case_when(TAY == 1 ~ "TAY",
TAY == 0 ~ "a_Non-TAY"))
clientCleanMR1 <- clientCleanMR1%>%
mutate(DestCoded = case_when(Destination == 22 ~ "a_Permanent",
Destination == 23 ~ "a_Permanent", Destination == 26 ~ "a_Permanent", Destination ==
28 ~ "a_Permanent", Destination == 19 ~ "a_Permanent", Destination == 3 ~
"a_Permanent", Destination == 31 ~ "a_Permanent",
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Destination == 33 ~ "a_Permanent", Destination == 34 ~ "a_Permanent", Destination == 10 ~ "a_Permanent", Destination == 20 ~ "a_Permanent", Destination == 21 ~ "a_Permanent", Destination == 11 ~ "a_Permanent", Destination == 18 ~ "Temporary",
Destination == 2 ~ "Temporary",
Destination == 32 ~ "Temporary",
Destination == 13 ~ "Temporary",
Destination == 36 ~ "Temporary",
Destination == 12 ~ "Temporary",
Destination == 35 ~ "Temporary",
Destination == 27 ~ "Temporary",
Destination == 15 ~ "Institutional",
Destination == 6 ~ "Institutional",
Destination == 7 ~ "Institutional",
Destination == 25 ~ "Institutional",
Destination == 4 ~ "Institutional",
Destination == 5 ~ "Institutional",
Destination == 16 ~ "Return to Homelessness", Destination == 1 ~ "Return to Homelessness", Destination == 14 ~ "Return to Homelessness", Destination == 18 ~ "Return to Homelessness", Destination == 29 ~ "Other",
Destination == 30 ~ "Other", Destination == 17 ~ "Other", Destination == 24 ~ "Other",
Destination == 37 ~ "Other",
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TESTS
Destination == 8 ~ "Other", Destination == 9 ~ "Other", Destination == 99 ~ "Other"))
T.Tests comparing Census to HMIS ## These tests tell us whether there are statistically significant demographic differences between the populations of Monterey and San Benito Counties
and individuals engaged with CHSP (and enrolled in HMIS) #### Bar Chart
# AmIndAKNative T.Test
AmIndTTest <- t.test(clientCleanMR$AmIndOnly, mu = 0.0017) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
AmIndTTest
# Asian T.Test
AsianTTest <- t.test(clientCleanMR$AsianOnly, mu = 0.0521) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
AsianTTest
Black T.Test

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BlackTTest <- t.test(clientCleanMR$BlackOnly, mu = 0.0222) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
BlackTTest
75

# PI T.Test
PITTest <- t.test(clientCleanMR$PIOnly, mu = 0.0038) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
PITTest
# White T.Test
WhiteTTest <- t.test(clientCleanMR$WhiteOnly, mu = 0.3002) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
WhiteTTest
# MultiRacial T.Test
MRTTest <- t.test(clientCleanMR$Multiracial, mu = 0.0275) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
MRTTest
# Latin(a/o) T.Test
LxTTest <- t.test(clientCleanMR$Ethnicity, mu = 0.5925) #For each of these t.tests, the "mu = " field must be manually entered. Mu is equal to the percentage of population with that racial/ethnic identity in Monterey/San Benito Counties.
LxTTest
# ***T.Test to measure TAY not possible because of separation of HoH and Spouse/Partner from Accompanied TAY.***
## Logistical Regressions ## These tests tell us whether there are statistically significant difference in destinations to which individuals enrolled in HMIS exit.
#Return to homelessness likelihood compared to Non-Latino, Non-TAY Whites.
76

m1 <- glm(DestCoded == "Return to Homelessness" ~ Multiracial + AmIndOnly + AsianOnly + BlackOnly + PIOnly + Ethnicity + TAY, data = clientCleanMR, family = "binomial")
summary(m1) exp(m1$coefficients)
#Multiracial return to homelessness vs non-multiracial return to homelessness
m1a <- glm(DestCoded == "Return to Homelessness" ~ Multiracial, data = clientCleanMR, family = "binomial")
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summary(m1a) exp(m1a$coefficients)
#American Indian return to homelessness vs non-American Indian return to
homelessness
m1b <- glm(DestCoded == "Return to Homelessness" ~ AmIndOnly, data =
clientCleanMR, family = "binomial")
summary(m1b) exp(m1b$coefficients)
#Asian return to homelessness vs non-asian return to homelessness
m1c <- glm(DestCoded == "Return to Homelessness" ~ AsianOnly, data =
clientCleanMR, family = "binomial")
summary(m1c) exp(m1c$coefficients)
#AfAm return to homelessness vs non-AfAm return to homelessness
m1d <- glm(DestCoded == "Return to Homelessness" ~ BlackOnly, data =
clientCleanMR, family = "binomial")
summary(m1d) exp(m1d$coefficients)
#Pacific ISlander return to homelessness vs non-PI return to homelessness
77

m1e <- glm(DestCoded == "Return to Homelessness" ~ PIOnly, data = clientCleanMR,
family = "binomial")
summary(m1e) exp(m1e$coefficients)
#White return to homelessness vs non-white return to homelessness
m1f <- glm(DestCoded == "Return to Homelessness" ~ WhiteOnly, data =
clientCleanMR, family = "binomial")
summary(m1f) exp(m1f$coefficients)
#Latino return to homelessness vs non-latino return to homelessness
m1g <- glm(DestCoded == "Return to Homelessness" ~ Ethnicity, data =
clientCleanMR, family = "binomial")
summary(m1g) exp(m1g$coefficients)
#TAY return to homelessness vs non TAY return to homelessness
m1h <- glm(DestCoded == "Return to Homelessness" ~ TAY, data = clientCleanMR,
family = "binomial") summary(m1h)
exp(m1h$coefficients)
#Permanent housing likelihood compared to non-latino, non-TAY whites.
m2 <- glm(DestCoded == "Permanent" ~ Multiracial + AmIndOnly + AsianOnly +
BlackOnly + PIOnly + Ethnicity + TAY, data = clientCleanMR, family = "binomial")
summary(m2) exp(m2$coefficients)
#Multiracial permanent housing vs non-multiracial permanent housing
m2a <- glm(DestCoded == "Permanent" ~ Multiracial, data = clientCleanMR, family =
"binomial")
78
```

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summary(m2a) exp(m2a$coefficients)
#American Indian permanent housing vs non-american indian permanent housing
m2b <- glm(DestCoded == "Permanent" ~ AmIndOnly, data = clientCleanMR, family =
"binomial") summary(m2b)
exp(m2b$coefficients)
#Asian permanent housing vs Asian permanent housing
m2c <- glm(DestCoded == "Permanent" ~ AsianOnly, data = clientCleanMR, family =
"binomial") summary(m2c)
exp(m2c$coefficients)
#AfAm permanent housing vs non-AfAm permanent housing
m2d <- glm(DestCoded == "Permanent" ~ BlackOnly, data = clientCleanMR, family =
"binomial") summary(m2d)
exp(m2d$coefficients)
m2e <- glm(DestCoded == "Permanent" ~ PIOnly, data = clientCleanMR, family =
"binomial") summary(m2e)
exp(m2e$coefficients)
m2f <- glm(DestCoded == "Permanent" ~ WhiteOnly, data = clientCleanMR, family =
"binomial") summary(m2f)
exp(m2f$coefficients)
m2g <- glm(DestCoded == "Permanent" ~ Ethnicity, data = clientCleanMR, family =
"binomial") summary(m2g)
exp(m2g$coefficients)
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m2h <- glm(DestCoded == "Permanent" ~ TAY, data = clientCleanMR, family =
"binomial") summary(m2h)
exp(m2h$coefficients)
m3 <- glm(DestCoded == "Temporary" ~ Multiracial + AmIndOnly + AsianOnly +
BlackOnly + PIOnly + Ethnicity + TAY, data = clientCleanMR, family = "binomial")
summary(m3) exp(m3$coefficients)
m3a <- glm(DestCoded == "Temporary" ~ Multiracial, data = clientCleanMR, family =
"binomial") summary(m3a)
exp(m3a$coefficients)
m3b <- glm(DestCoded == "Temporary" ~ AmIndOnly, data = clientCleanMR, family =
"binomial") summary(m3b)
exp(m3b$coefficients)
m3c <- glm(DestCoded == "Temporary" ~ AsianOnly, data = clientCleanMR, family =
"binomial") summary(m3c)
exp(m3c$coefficients)
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m3d <- glm(DestCoded == "Temporary" ~ BlackOnly, data = clientCleanMR, family =
"binomial") summary(m3d)
exp(m3d$coefficients)
m3e <- glm(DestCoded == "Temporary" ~ PIOnly, data = clientCleanMR, family =
"binomial") summary(m3e)
exp(m3e$coefficients)
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m3f <- glm(DestCoded == "Temporary" ~ WhiteOnly, data = clientCleanMR, family =
"binomial") summary(m3f)
exp(m3f$coefficients)
m3g <- glm(DestCoded == "Temporary" ~ Ethnicity, data = clientCleanMR, family =
"binomial") summary(m3g)
exp(m3g$coefficients)
m3h <- glm(DestCoded == "Temporary" ~ TAY, data = clientCleanMR, family =
"binomial") summary(m3h)
exp(m3h$coefficients)
m4 <- glm(DestCoded == "Institutional" ~ Multiracial + AmIndOnly + AsianOnly +
BlackOnly + PIOnly + Ethnicity + TAY, data = clientCleanMR, family = "binomial")
summary(m4) exp(m4$coefficients)
m4a <- glm(DestCoded == "Institutional" ~ Multiracial, data = clientCleanMR, family =
"binomial") summary(m4a)
exp(m4a$coefficients)
m4b <- glm(DestCoded == "Institutional" ~ AmIndOnly, data = clientCleanMR, family =
"binomial") summary(m4b)
exp(m4b$coefficients)
m4c <- glm(DestCoded == "Institutional" ~ AsianOnly, data = clientCleanMR, family =
"binomial") summary(m4c)
exp(m4c$coefficients)
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m4d <- glm(DestCoded == "Institutional" ~ BlackOnly, data = clientCleanMR, family =
"binomial") summary(m4d)
exp(m4d$coefficients)
m4e <- glm(DestCoded == "Institutional" ~ PIOnly, data = clientCleanMR, family =
"binomial") summary(m4e)
exp(m4e$coefficients)
m4f <- glm(DestCoded == "Institutional" ~ WhiteOnly, data = clientCleanMR, family =
"binomial") summary(m4f)
exp(m4f$coefficients)
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m4g <- glm(DestCoded == "Institutional" ~ Ethnicity, data = clientCleanMR, family = "binomial") summary(m4g)
exp(m4g$coefficients)
m4h <- glm(DestCoded == "Institutional" ~ TAY, data = clientCleanMR, family = "binomial") summary(m4h)
exp(m4h$coefficients)
m5 <- glm(DestCoded == "Other" ~ Multiracial + AmIndOnly + AsianOnly + BlackOnly + PIOnly + Ethnicity + TAY, data = clientCleanMR, family = "binomial")
summary(m5) exp(m5$coefficients)
m5a <- glm(DestCoded == "Other" ~ Multiracial, data = clientCleanMR, family = "binomial") summary(m5a)
exp(m5a$coefficients)
82

m5b <- glm(DestCoded == "Other" ~ AmIndOnly, data = clientCleanMR, family = "binomial") summary(m5b)
exp(m5b$coefficients)
m5c <- glm(DestCoded == "Other" ~ AsianOnly, data = clientCleanMR, family = "binomial") summary(m5c)
exp(m5c$coefficients)
m5d <- glm(DestCoded == "Other" ~ BlackOnly, data = clientCleanMR, family = "binomial") summary(m5d)
exp(m5d$coefficients)
m5e <- glm(DestCoded == "Other" ~ PIOnly, data = clientCleanMR, family = "binomial")
summary(m5e)
exp(m5e$coefficients)
m5f <- glm(DestCoded == "Other" ~ WhiteOnly, data = clientCleanMR, family = "binomial") summary(m5f)
exp(m5f$coefficients)
m5g <- glm(DestCoded == "Other" ~ Ethnicity, data = clientCleanMR, family = "binomial") summary(m5g)
exp(m5g$coefficients)
m5h <- glm(DestCoded == "Other" ~ TAY, data = clientCleanMR, family = "binomial")
summary(m5h)
exp(m5h$coefficients)
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##ROC Curves for LogRegs## #model 1
class1 <- m1$y
score1 <- qlogis(m1$fitted.values) roc1 <- rocit(score = score1,

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class = class1, method = "bin")
plot(roc1, col=c("red", "green")) roc1
#model 1a
class1a <- m1$ya
score1a <- qlogis(m1a$fitted.values) roc1a <- rocit(score = score1a,
class = class1a, method = "bin")
plot(roc1a, col=c("red", "green")) roc1a
#model 1b
class1b <- m1b$y
score1b <- qlogis(m1b$fitted.values) roc1b <- rocit(score = score1b,
class = class1b, method = "bin")
plot(roc1b, col=c("red", "green"))
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roc1b
#model 1c
class1c <- m1c$y
score1c <- qlogis(m1c$fitted.values) roc1c <- rocit(score = score1c,
class = class1c, method = "bin")
plot(roc1c, col=c("red", "green")) roc1c
#model 1d
class1d <- m1d$y
score1d <- qlogis(m1d$fitted.values) roc1d <- rocit(score = score1d,
class = class1d, method = "bin")
plot(roc1d, col=c("red", "green")) roc1d
#model 1e
class1e <- m1e$y
score1e <- qlogis(m1e$fitted.values) roc1e <- rocit(score = score1e,
class = class1e, method = "bin")
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plot(roc1e, col=c("red", "green")) roc1e
#model 1f
class1f <- m1f$y
score1f <- qlogis(m1f$fitted.values) roc1f <- rocit(score = score1f,
class = class1f, method = "bin")
plot(roc1f, col=c("red", "green")) roc1f
#model 1g
class1g <- m1g$y
score1g <- qlogis(m1g$fitted.values) roc1g <- rocit(score = score1g,
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class = class1g, method = "bin")
plot(roc1g, col=c("red", "green")) roc1g
#model 1h
class1h <- m1h$y
score1h <- qlogis(m1h$fitted.values) roc1h <- rocit(score = score1h,
class = class1h, method = "bin")
86

plot(roc1h, col=c("red", "green")) roc1h
#model 2
class2 <- m2$y
score2 <- qlogis(m2$fitted.values) roc2 <- rocit(score = score2,
class = class2, method = "bin")
plot(roc2, col=c("red", "green")) roc2
#model 2a
class2a <- m2a$y
score2a <- qlogis(m2a$fitted.values) roc2a <- rocit(score = score2a,
class = class2a, method = "bin")
plot(roc2a, col=c("red", "green")) roc2a
#model 2b
class2b <- m2b$y
score2b <- qlogis(m2b$fitted.values) roc2b <- rocit(score = score2b,
class = class2b,
87

method = "bin")
plot(roc2b, col=c("red", "green")) roc2b
#model 2c
class2c <- m2c$y
score2c <- qlogis(m2c$fitted.values) roc2c <- rocit(score = score2c,
class = class2c, method = "bin")
plot(roc2c, col=c("red", "green")) roc2c
#model 2d
class2d <- m2d$y
score2d <- qlogis(m2d$fitted.values) roc2d <- rocit(score = score2d,
class = class2d, method = "bin")
plot(roc2d, col=c("red", "green")) roc2d
#model 2e
class2e <- m2e$y
score2e <- qlogis(m2e$fitted.values) roc2e <- rocit(score = score2e,
```

88

```
class = classe2, method = "bin")
plot(roc2e, col=c("red", "green")) roc2e
#model 2f
class2f <- m2f$y
score2f <- qlogis(m2f$fitted.values) roc2f <- rocit(score = score2f,
class = class2f, method = "bin")
plot(roc2f, col=c("red", "green")) roc2f
#model 2g
class2g <- m2g$y
score2g <- qlogis(m2g$fitted.values) roc2g <- rocit(score = score2g,
class = class2g, method = "bin")
plot(roc2g, col=c("red", "green")) roc2g
#model 2h
class2h <- m2$yh
score2h <- qlogis(m2h$fitted.values)
```

89

```
roc2h <- rocit(score = score2h, class = class2h,
method = "bin")
plot(roc2h, col=c("red", "green")) roc2h
#model 3
class3 <- m3$y
score3 <- qlogis(m3$fitted.values) roc3 <- rocit(score = score3,
class = class3, method = "bin")
plot(roc3, col=c("red", "green")) roc3
#model 3a
class3a <- m3a$y
score3a <- qlogis(m3a$fitted.values) roc3a <- rocit(score = score3a,
class = class3a, method = "bin")
plot(roc3a, col=c("red", "green")) roc3a
#model 3b class3b <- m3b$y
```

90

```
score3b <- qlogis(m3b$fitted.values) roc3b <- rocit(score = score3b,
class = class3b, method = "bin")
plot(roc3b, col=c("red", "green")) roc3b
#model 3c
class3c <- m3c$y
```

```
score3c <- qlogis(m3c$fitted.values) roc3c <- rocit(score = score3c,
class = class3c, method = "bin")
plot(roc3c, col=c("red", "green")) roc3c
#model 3d
class3d <- m3d$y
score3d <- qlogis(m3d$fitted.values) roc3d <- rocit(score = score3d,
class = class3d, method = "bin")
plot(roc3d, col=c("red", "green")) roc3d
#model 3e
91

class3e <- m3e$y
score3e <- qlogis(m3e$fitted.values) roc3e <- rocit(score = score3e,
class = class3e, method = "bin")
plot(roc3, col=c("red", "green")) roc3
#model 3f
class3f <- m3f$y
score3f <- qlogis(m3f$fitted.values) roc3f <- rocit(score = score3f,
class = class3f, method = "bin")
plot(roc3f, col=c("red", "green")) roc3f
#model 3g
class3g <- m3g$y
score3g <- qlogis(m3g$fitted.values) roc3g <- rocit(score = score3g,
class = class3g, method = "bin")
plot(roc3g, col=c("red", "green")) roc3g
92

#model 3h
class3h <- m3h$y
score3h <- qlogis(m3h$fitted.values) roc3h <- rocit(score = score3h,
class = class3h, method = "bin")
plot(roc3h, col=c("red", "green")) roc3h
#model 4
class4 <- m4$y
score4 <- qlogis(m4$fitted.values) roc4 <- rocit(score = score4,
class = class4, method = "bin")
plot(roc4, col=c("red", "green")) roc4
#model 4a
class4a <- m4a$y
score4a <- qlogis(m4a$fitted.values) roc4a <- rocit(score = score4a,
```

```
class = class4a, method = "bin")
plot(roc4a, col=c("red", "green")) roc4a
93

#model 4b
class4b <- m4b$y
score4b <- qlogis(m4b$fitted.values) roc4b <- rocit(score = score4b,
class = class4b, method = "bin")
plot(roc4b, col=c("red", "green")) roc4b
#model 4c
class4c <- m4c$y
score4c <- qlogis(m4c$fitted.values) roc4c <- rocit(score = score4c,
class = class4c, method = "bin")
plot(roc4c, col=c("red", "green")) roc4c
#model 4d
class4d <- m4d$y
score4d <- qlogis(m4d$fitted.values) roc4d <- rocit(score = score4d,
class = class4d, method = "bin")
plot(roc4d, col=c("red", "green"))
94

roc4d
#model 4e
class4e <- m4e$y
score4e <- qlogis(m4e$fitted.values) roc4e <- rocit(score = score4e,
class = class4e, method = "bin")
plot(roc4e, col=c("red", "green")) roc4e
#model 4f
class4f <- m4f$y
score4f <- qlogis(m4f$fitted.values) roc4f <- rocit(score = score4f,
class = class4f, method = "bin")
plot(roc4f, col=c("red", "green")) roc4f
#model 4g
class4g <- m4g$y
score4g <- qlogis(m4g$fitted.values) roc4g <- rocit(score = score4g,
class = class4g, method = "bin")
95

plot(roc4g, col=c("red", "green")) roc4g
#model 4h
```

```
class4h <- m4h$y
score4h <- qlogis(m4h$fitted.values) roc4h <- rocit(score = score4h,
class = class4h, method = "bin")
plot(roc4h, col=c("red", "green")) roc4h
#model 5
class5 <- m5$y
score5 <- qlogis(m5$fitted.values) roc5 <- rocit(score = score5,
class = class5, method = "bin")
plot(roc5, col=c("red", "green")) roc5
#model 5a
class5a <- m5a$y
score5a <- qlogis(m5a$fitted.values) roc5a <- rocit(score = score5a,
class = class5a, method = "bin")
```



```
plot(roc5a, col=c("red", "green")) roc5a
#model 5b
class5b <- m5b$y
score5b <- qlogis(m5b$fitted.values) roc5b <- rocit(score = score5b,
class = class5b, method = "bin")
plot(roc5b, col=c("red", "green")) roc5b
#model 5c
class5c <- m5c$y
score5c <- qlogis(m5c$fitted.values) roc5c <- rocit(score = score5c,
class = class5c, method = "bin")
plot(roc5c, col=c("red", "green")) roc5c
#model 5d
class5d <- m5d$y
score5d <- qlogis(m5d$fitted.values) roc5d <- rocit(score = score5d,
class = class5d,
```



```
method = "bin")
plot(roc5d, col=c("red", "green")) roc5d
#model 5e
class5e <- m5e$y
score5e <- qlogis(m5e$fitted.values) roc5e <- rocit(score = score5e,
class = class5e, method = "bin")
plot(roc5e, col=c("red", "green")) roc5e
#model 5f
```

```
class5f <- m5f$y
score5f <- qlogis(m5f$fitted.values) roc5f <- rocit(score = score5f,
class = class5f, method = "bin")
plot(roc5f, col=c("red", "green")) roc5f
#model 5g
class5g <- m5g$y
score5g <- qlogis(m5g$fitted.values) roc5g <- rocit(score = score5g,
98

class = class5g, method = "bin")
plot(roc5g, col=c("red", "green")) roc5g
#model 5h
class5h <- m5h$y
score5h <- qlogis(m5h$fitted.values) roc5h <- rocit(score = score5h,
class = class5h, method = "bin")
plot(roc5h, col=c("red", "green")) roc5h
#test MR for length
MR1 <- lm(Length ~ Race + TAY1, data = clientCleanMR1) summary(MR1)
MR2 <- lm(Length ~ Race + TAY1 + DestCoded, data = clientCleanMR1)
summary(MR2)
MR3 <- lm(Length ~ Race + TAY1 + as.factor(Destination), data = clientCleanMR1)
summary(MR3)
```

Annotated Bibliography

(n.d.). (rep.). *Lake County Continuum of Care 2020-2021 Two Year Strategic Plan Report*. Retrieved May 12, 2022, from https://www.lakecoc.org/_files/ugd/1f97da_4e7c61a6929a4e6faffc2d641eab4443.pdf.

This report outlines Lake County Continuum of Care's strategic plan for the next two fiscal years. High-level goals include 1) developing organization structural priorities (like finalizing HMIS contract, developing a coordinated entry system, soliciting counsel for consolidated applications, expanding CoC membership, and strengthening equity), 2) creating goals and strategies in providing housing (like providing shelters around the County with support and assistance).

(n.d.). (rep.). *Lake County Continuum of Care Gap Analysis Report*. Retrieved from https://www.lakecoc.org/_files/ugd/1f97da_f26c8deea386460b82e744ee4ad8f3fc.pdf.

This gap analysis outlines gaps in Lake County CoCs operations and programming. Some gaps include a functioning coordinated entry system, personnel gaps, and funding opportunities for housing solutions (broken down demographically by age, race, ethnicity, and socioeconomic status).

2021 AHAR: Part 1 - pit estimates of homelessness in the U.S. 2021 AHAR: Part 1 - PIT Estimates of Homelessness in the U.S. | HUD USER. (n.d.). Retrieved May 12, 2022, from https://www.huduser.gov/portal/datasets/ahar/2021-ahar-part-1-pit-estimates-of-homelessness-in-the-us.html

This report outlines the key findings of the Point-In-Time (PIT) count and Housing Inventory Count (HIC) conducted in January 2021. Specifically, this report provides 2021 national, state, and CoC-level PIT and HIC estimates of homelessness, as well as estimates of chronically homeless persons, homeless veterans, and homeless children and youth.

The alliance's racial equity network toolkit. National Alliance to End Homelessness. (2021, March 17). Retrieved May 12, 2022, from https://endhomelessness.org/resource/the-alliances-racial-equity-network-toolkit/

This toolkit outlines the National Alliance to End Homelessness' best practices for addressing racial disparities in homeless populations. The toolkit was built by their Raciety Equity Network (REN) and is broken up into practices for assessing disproportionality and disparity, as well as disparate outcomes.

Business, C. S. and H. A. (n.d.). *Acting to prevent, reduce and end homelessness*. CA.gov. Retrieved May 12, 2022, from https://bcsh.ca.gov/calich/hdis.html

Interactive data visualization and informational hub on racial disparities in homeless provided by the State of CA. Includes demographic breakdowns of all 44 in-state Continuums of Care.

COC analysis tool: Race and ethnicity. HUD Exchange. (n.d.). Retrieved May 12, 2022, from https://www.hudexchange.info/resource/5787/coc-analysis-tool-race-and-ethnicity/

The CoC Analysis Tool: Race and Ethnicity draws on Point-In-Time Count (PIT) and American Community Survey (ACS) data to facilitate the analysis of racial disparities among people experiencing homelessness. Such an analysis is a critical first step in identifying and changing racial and ethnic disparities in our systems and services.

Continuum of Care (COC) program. HUD Exchange. (n.d.). Retrieved May 12, 2022, from https://www.hudexchange.info/programs/coc/

Informational hub on the HUD website explaining the Continuum of Care program and how it is implemented throughout the country. Has links to access individual state resources.

Crawford, C. (2021, September 20). *Analyzing racial disparities in the homelessness system: We need to get moving. the Nofo tells us how*. National Alliance to End Homelessness. Retrieved May 12, 2022, from https://endhomelessness.org/blog/analyzing-racial-disparities-in-the-homelessness-system-we-need-to-get-moving-the-nofo-tells-us-how/

Outlines the U.S. Department of Housing & Urban Development's (HUD) prioritization of racial equity in this year's Notice of Funding Opportunity (NOFO). The article highlights that Continuums of Care (CoCs) are incentivized to assess their homelessness programs and systems for racial disparities in services and outcomes, to assess barriers, and develop action plans if inequities are found.

Ending homelessness - Santa Clara County, California. (n.d.). Retrieved May 12, 2022, from https://housingtoolkit.sccgov.org/sites/g/files/exjcpb501/files/SCC%20Community%20Plan%20to%20End%20Homelessness%20-%20Executive%20Summary_FINAL.pdf

An infographic showcasing Santa Clara County's progress on strategic goals and next steps.

How we should talk about racial disparities. Urban Institute. (2020, February 26). Retrieved May 12, 2022, from https://www.urban.org/urban-wire/how-we-should-talk-about-racial-disparities

This article outlines the context of the United States' most recent racial awakening in June 2020 after the murder of George Floyd, and how this has catalyzed a major movement to analyze how we view and respond to racial inequities in this country.

Lead me home plan update - chsp.org. Coalition of Homeless Service Providers. (n.d.). Retrieved May 12, 2022, from https://chsp.org/wp-content/themes/chsp/img/Monterey-and-San-Benito-Counties-5YP_LMH-Update_07232021.pdf

The Coalition of Homeless Service Providers 5-year plan to address and minimize the issue of homeless in Monterey and San Benito Counties. Provides a current snapshot of where Monterey and San Benito County sit in terms of their homeless population by numbers and descriptive statistics. Provides the vision and guiding principles for the 5-year strategy to end homelessness, as well as a monitoring and evaluation plan.

Schonfeld, B. (2020, August 14). *How to Study Racial Disparities*. Scientific American. Retrieved May 12, 2022, from https://www.scientificamerican.com/article/how-to-study-racial-disparities/

An opinion piece on how to go about understanding the root causes of unequal treatment of individuals based on race and ethnicity throughout our country's infrastructural systems. Explains the importance of statistical, conceptual, and historical complexities associated with race.

Social Justice: Racial disparity. HUSL Library. (n.d.). Retrieved May 12, 2022, from https://library.law.howard.edu/socialjustice/disparity#:~:text=Racial%20disparity%20refers%20to%20the,aspects%20of%20life%20and%20society

Explains the concept of racial disparities, how they come to exist, information on other resources to learn about them, and suggestions on how to address them.