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The Processing and Visualization of Homelessness Data Collected During the Annual Point-in-Time Count

Author
Tkachenko, Ulyana

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THE PROCESSING AND VISUALIZATION OF HOMELESSNESS DATA COLLECTED DURING THE ANNUAL POINT-IN-TIME COUNT

By

Ulyana Tkachenko

A capstone project submitted for
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University Honors
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APPROVED

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Dr.Paea LePendu
Department of Computer Science, Bournes College of Engineering

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Dr. Richard Cardullo, Howard H Hays Jr. Chair, University Honors

Abstract

Over the last two years, UCR's Team of Undergraduate Research Students (RCHI) has collaborated with the County of Riverside to help optimize data processing and visualization for Unsheltered data collected in the annual Point In Time Count (PIT). The key goal of the project was to construct an autonomous dataflow pipeline that would take in raw data from the count, process it accurately and efficiently, and create detailed visualizations of the aggregate information. Python programs were created to handle the data processing steps: data joining, identification and removal of invalid data, and data aggregation. Each step was manually tested on the 2019 and 2020 data for maximum confidence in the accuracy of the code. Joined data files were mathematically and visually inspected, identified invalid data was logged and its removal was validated, and data aggregation was cross-checked in multiple ways. Visualizations of the data were created by combining pie/bar/line graphs and tables into informative dashboards. For the 2019 Point In Time Count, RCHI produced 7 unique Tableau dashboards that displayed a total of 45 various charts, 60% more than the county produced in 2018. In the following year, RCHI created an open-source website with replicated original dashboards and 3 new ones. The 10 unique dashboards presented in 2020 were composed of 57 dynamic charts that provided detailed information on county, city, and supervisorial district levels. Efficiency was measured by the level of autonomy within the code. By 2020, manual data handling was required for only 3 main steps: validating self-input living situations, identifying survey locations, and pushing the data into the website back-end server. This report describes the evolution of the project's data pipeline over the last two years and analyzes its success in creating an accurate, effective, and in-depth data analytics platform.

Acknowledgments

I would like to give my sincerest thanks to my professor, boss, and above all, mentor Professor Paea LePendu. His dedication and support have made possible the projects I completed during my undergraduate study and helped me grow into a better person.

I would also like to thank the County of Riverside Department of Public Social Services and their Continuum of Care department. This project would not be possible without their dedication to helping alleviate homelessness within Riverside County and an open mind to searching for innovative solutions to do so.

I would like to thank my UCR Undergraduate Research Team (Riverside County Health Informatics) for their invaluable contributions towards this project. Thank you, Kevin Frasier, Francisco Gallego, Kevin Ferrer, Cameron Morin, Itzel Gonzales, Cindy Chen, Josiah Lee, Jerry Tan, Kamaljot Singh, Paris Hom, Pamodya Peiris, and Logan Crocker.

` It has been an absolute pleasure to work with you all and I wish you nothing but the best in your future endeavors.

Most importantly, I would like to thank and recognize my wonderful mom and dad in their unwavering support and encouragement for everything I do. Without their dedication, I would still be repeating kindergarten instead of graduating UCR.

Individual Contribution

This report discusses and analyzes an Undergraduate Research Project completed over the course of two years by an Undergraduate Computer Science and Engineering student team called Riverside County Health Informatics (RCHI). Over the 2-year timeframe, the team has had 13 different students contributing to the project's success. At the project's peak, the team was composed of 9 individual team members.

I have led this project since it was first founded in 2018. As a team leader, I volunteered in Riverside County's Annual Point-In-Time Count, helped manage the project budget, divide work, and attend Riverside County meetings to discuss the project's progress. I formally presented the project in the following events:

- 2019 Undergraduate Research Symposium Poster Presentation
- 2019 Riverside County Point-In-Time Count Comunity Debrief
- 2019 UCR GIS Day Panel Presentation
- 2020 Riverside County Point-In-Time Count Comunity Debrief

Although this report discusses the project as a whole, analysis of the work that I was directly responsible for is discussed with a much higher level of detail. My most major contributions to the project are as follows:

- 2019 Tableau Dashboard Design and Compilation (Winter-Spring 2019)
- 2019-2020 Python Data Counting Scripts (Summer 2019-Fall 2020)
- 2020 Data Cleaning and Deduplication Scripts (Summer 2019-Winter 2020)

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Introduction

Prior to 2018, Riverside County conducted the annual Point-In-Time Count of the homeless population using paper surveys and manually tallied the totals necessary for federal reporting. This method was time-consuming and error-prone. By the following year, the survey process shifted from paper format to an online Survey 1-2-3 App which automated raw data collection and recorded new metadata such as timestamp and GPS coordinates of the PIT surveys. For the 2019 Point-In-Time Count, Riverside County's Continuum of Care partnered with UCR's Bourns College of Engineering to develop and deploy a data science platform to process this new data and ultimately streamline the count.

The key goals of the project were to increase the efficiency, accuracy, and visual representation of the data collected by the Point-In-Time count. A data flow pipeline was selected to segment the data handling process into multiple parts. In 2019, my team and I focused on automating data counting and creating a set of dashboards that visually displayed the aggregate data through a data analysis program called Tableau. By the 2020 PIT count, the majority of the data handling process was successfully automated. Automation for the data processing algorithms increased accuracy and data handling was improved to work with any year, increasing efficiency of upcoming counts. Data visualization was upgraded from relying on the Tableau platform to an open-source website, with several new dashboards and charts. This report discusses the methodology used to achieve key goals, the extent of success in achieving them and goes over the resulting dashboards.

Background

Every year, the Federal Department of Housing and Urban Development (HUD) mandates Continuum of Care (CoC) organizations to count and report the number of individuals experiencing homelessness within their respective counties. This annual count is known as the Point-In-Time (PIT) count and takes place over the course of a week in January. Data collected during the count provides crucial feedback to organizations working to alleviate homelessness, allowing them to efficiently plan and manage their programs. Additionally, federal funding for homelessness programs is distributed to counties on the basis of these counts. Each CoC department is tasked with collecting some standardized demographic and subpopulation information during the count, however, the organizational details of the count are left up to the counties themselves.

PIT Count Survey Process

The Point-In-Time count is broken into two main sub-counts: sheltered and unsheltered, with the two counts occurring in parallel. The "Sheltered" count is focused on homeless individuals that are semi-permanently sheltered during the time of the count. Semi-permanent shelters include places such as hospitals, emergency shelters, transitional housing projects, and Safe Haven locations. The unsheltered count is conducted by community volunteers going out and recording information on the homeless population living outside without adequate shelter and is further broken down into two separate categories: observational and interview. When a volunteer encounters a homeless individual, their primary goal is to conduct an interview to collect the most detailed and accurate information about the individual. This interaction is classified as an "Unsheltered Interview" count. In some cases (the homeless individual being in an unreachable location, refusing to interview, etc.) an interview is not possible so the volunteer notes down observable demographic details of the individual instead. This interaction is classified as an "Unsheltered Observational" count. The full breakdown of the categories is shown below (Fig.1). This project only processes the raw "Unsheltered" data gathered from the survey app. Mentioned "Sheltered" data was provided by the County in post-processed, aggregate form.

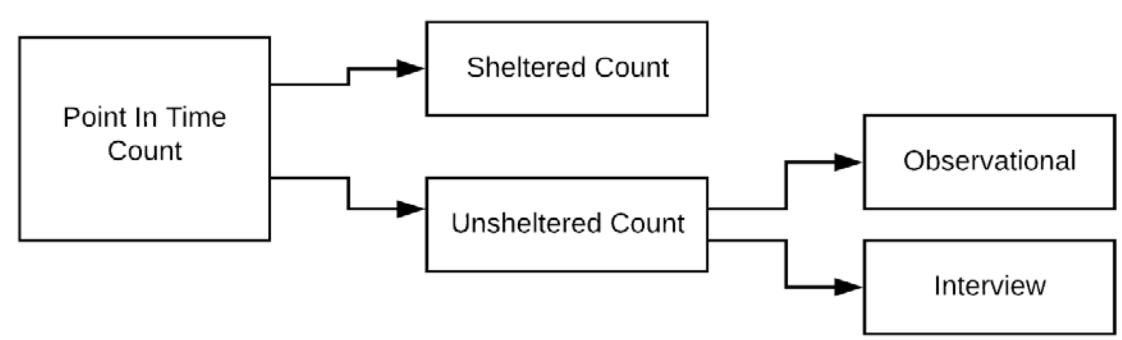


Fig. 1, Point-In-Time Count Category Breakdown

HUD requirements for the information collected during the count are broken down into two main categories: demographic and subpopulation data. Demographic data consist of information regarding gender, age, race, ethnicity, and living situations. Subpopulation data consist of counting individuals who are veterans, chronically homeless, on veteran medical assistance, or with a disabling condition. Additionally, HUD mandated the count keeps track of three main homeless household types. Households are defined by a group of one or more homeless individuals living together and the types are broken down as follows; persons in households with at least one adult and one child, persons in households without children and persons in households with only children. Questions a volunteer has to answer slightly differ between the observational and interview surveys. The observational survey has preset answers for each category with an additional answer of “Unknown” if the volunteer is unsure of the answer. In contrast, an interview survey allows for manual input for exact data in demographic categories like “Age” and “Living Situation”. An unknown option is still included in the chance the homeless individual is unsure or unable to answer. A comprehensive graph containing all the survey categories used throughout the project is in the appendix (Fig. B1) in addition to the survey instrument used for the 2019 PIT counts (Fig. B8).

Methodology

RCHI received the raw data gathered from the 2019 and 2020 Unsheltered Point-In-Time Count surveys that needed to be checked, processed, and then visually displayed. The data flow for this project was decided as follows (Fig. 2). Significant improvements to streamlining the pipeline from 2019 to 2020 have been made. In 2019, data had to be manually transferred over into each subsequent step of the process. By the 2020 PIT Count, two python programs were built to handle multiple steps of the process and only required a single manual data transfer- greatly optimizing the data flow. The individual approaches of the two years are outlined below.

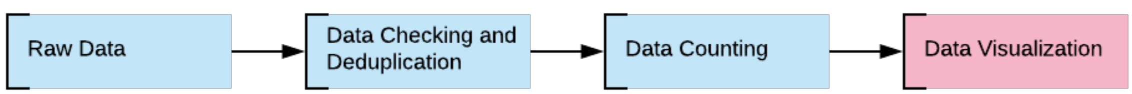


Fig. 2, General Data Pipeline

Raw Data

The initial data the UCR team received came directly from the 1-2-3 Survey App used by volunteers to record information during the Unsheltered Count. This data was formatted as two spreadsheets where each column is a single survey question and each row represented a single homeless individual, with the respective columns containing the survey answers for that individual. Homeless individuals were differentiated by a unique GlobalID. Within this report, each row is referenced as a *data point*. During the survey, volunteers had the option to interview or observe more than one homeless individual from the same group. The first spreadsheet contained basic information from the initial persons while the second spreadsheet contained information from subsequent individuals as well as in-depth information on the initial interviewee. The two spreadsheets were tied together by a shared GlobalID of the initially interviewed persons, with the subsequent sheet also containing individual UniqueID's for each additional group member. Finally, the raw data contained temporal and spatial metadata gathered during the survey's start internally by the app.

Data Checking and Deduplication Process

The initial step in the data cleaning process combines the information from both spreadsheets to gain a holistic view of each homeless individual. The spreadsheets were joined together through an outer join on the GlobalID parameter. The subsequent spreadsheet was then checked for data validation and invalid data points were removed. Invalid entries are defined by HUD standards as surveys that occur outside the survey time zone or location, incomplete surveys, surveys of individuals who are not considered homeless, surveys with corrupted data, and multiple surveys of the same individual. The removal of the latter is defined as the *deduplication process.* Each invalid data point is logged into a master remove log for historical reference and manual checking. After checking is complete, the dataset is considered clean and moved along to the next step of the pipeline. The methodology for joining the data, checking for validity, deduplication, and logging differed by year and is separately outlined below.

2019 Data Cleaning Steps

1. **Data Joining.** The two spreadsheets were joined through an online data visualization software called Tableau.

2. **Data Checking.** The resulting spreadsheet was checked manually to ensure the accuracy of the outer-join. Data points that did not have an initial GlobalID were removed because they were invalid. Afterward, the data were checked using small python scripts, logic operations, and excel spreadsheets. A python script was used to take the GPS coordinates for each data point and attribute them to a certain location. Data that fell outside of the date, time, and location range was removed. Individuals whose "Living Situation" is not considered homeless were identified by hand and removed.
3. **Data Deduplication.** Data deduplication happened manually, using an excel spreadsheet. If all 5 categories for two data points were identical, the individual was removed.

The Remove Log

All invalid data points and the reason for their removal was manually imputed into a master remove-log. A statistical summary of the log is presented below.

Removal Reason	Number Removed
Invalid Survey Date/Time	269
Invalid Survey Location	1
Invalid Survey Type	46
Living Situation Not Valid For PIT Count	44
Unknown Living Situation	4
Incomplete Information	7
Duplicate Entry of Same Persons	75
Total Data Points Removed	**446**

Fig 3, 2019 PIT Data Remove Log Statistical Summary

2020 Data Cleaning Steps

A single python program was created that handles the data joining, checking, and deduplication process and compiles several logs detailing the changes made in the data. This program relies on Pandas and Numpy libraries to optimize dealing with the dataset and is capable of completing all data manipulation in a matter of seconds, significantly faster than in the previous year. Manually identifying and removing invalid data points was necessary for only one survey category- Self-Identified Living Situations. This program was created with subsequent years in mind and could be quickly manipulated to process the PIT count data for many years to come.

1. **Data Joining.** The first part of the python program focuses on the data joining process. It took in both spreadsheets as input, joined them, checked the accuracy of the outer-join by making sure the matched GlobalDs were identical. The subsequently joined data was then subject to a data checking algorithm
2. .**Data Checking.** Immediately after joining the two spreadsheets, the software began checking the validity of the data. The columns of each individual data row were checked against a list of issues (Fig. 4).

Issue For Removal	Issues For Checking
Invalid Survey Date/Time	Self-Identified Living Situation
Invalid Survey Location	
Invalid/Unknown Survey Type	
Living Situation Not Valid For PIT Count	
Unknown Living Situation	
Incomplete Survey Information	
Duplicate Entry of Same Persons	

Fig. 4, 2020 List of Issues That Make A Datapoint Invalid

Rows that contained these issues were marked invalid and logged into issue-specific removal logs. After the checking was complete, all data points included in the master log were removed automatically. Accuracy was ensured by mathematically comparing the sizes of the dataset and log during each step to ensure the correct amount of points were removed. The new dataset was outputted in addition to the check-log that contains all data points with self-identified living situations. After manual removal of the invalid self-identified living situations, the data set is cleaned and complete.

3. **Data Deduplication** happened fully autonomously. The program compared each data point to every other data point using the recommended survey question categories (Appendix A1). If all six survey answers were identical, the first survey was kept as the original and subsequent identical surveys were flagged as duplicates and added to the remove log.

Remove and Check Logs

During runtime, the program automatically compiled two types of logs with information about the data: check and remove logs. The check log contained every survey that had a self-identified living situation- meaning the answer was imputed manually instead of being one of the few provided options. Human judgment was needed to decide if the answer matched HUD's criteria for an unsheltered homeless individual (Appendix A2), and if not, the data point had to be removed manually from the dataset. Individual remove logs for each issue were automatically compiled and then combined together into a master remove log. made up of lists of rows that contained the specific issue. This master log contained a list of every data point subject to removal, reason, and proof from the specific column causing the issue. These points were automatically removed from the dataset and it was deemed clean. A statistical summary of the individual remove logs is available in the appendix (Fig. B3) The master remove log summary is shown below (Fig. 5).

Removal Reason	Number Removed
Invalid Survey Date/Time	165
Invalid Survey Location	8
Invalid Survey Type	0
Living Situation Not Valid For PIT Count	43
Unknown Living Situation	0
Incomplete Interview Information	274
Incomplete Observational Information	91
Duplicate Entry of Same Persons	57
Total Data Points Removed	**638**

Fig. 5, 2020 PIT Data Remove Log Statistical Summary

Data Counting Process

The cleaned dataset then had to be manipulated from its original form into totals of all individual data elements used by the final visualizations. Prior to UCR's involvement, the totals were calculated using excel every year. Our team developed a dynamic solution to PIT data that removes the need for an annual repeat of the counting process because it is capable of quickly totaling data for any given year. To ensure accuracy, multiple python scripts were written for each subcategory to separately count and cross-check totals. In 2019, script results were collaboratively compiled into a single spreadsheet that was then uploaded to Tableau, the data analytics software we used for creating charts and graphs that year. By 2020, these individual python scripts were combined into a single program that took in the cleaned dataset and aggregated all the necessary data element totals into csv and json files that were required by the new format of visualizations. The final counting script was cross-checked with both 2019 and 2020 data for accuracy and backward compatibility.

Data Visualization Process

Prior to UCR's involvement, Riverside County provided a limited amount of static visualizations for the Point-In-Time data (Fig. B2). The main goal of this project was to improve on the infographic by providing in-depth, comprehensive, and dynamic visualizations that reflected the majority of the survey information gathered during the Point-In-Time Count. For both years, UCR produced several dynamic visualizations, called *dashboards*, that contained a compilation of charts and graphs on the aggregate data.

2019 Tableau Dashboards

For the 2019 Point-In-Time count, we constructed these visualizations through a data analytics software called Tableau (Fig. C1-C7). Tableau internally handled two key processes; online hosting of the data used for the visualizations and publishing the finalized dashboards online, making it a great choice to get familiar with the project data. The dashboards were constructed by combining charts and graphs that were individually created using the imported data counts. The information shown on each dashboard was determined in close collaboration with the County to best suit the needs of different departments and organizations. In the process of working with Tableau, however, limitations came up (e.g. the difficulty of importing subsequent year data, inability to work collaboratively, manual creation of charts and graphs) that suggested a need to move away from the platform in the upcoming years.

2020 Open-Source Website Dashboards

For the 2020 PIT Count, RCHI advanced to constructing the dashboards from scratch. Aggregate data was stored in an online server securely hosted by the school and visualized on an open-source website created by UCR's team. Deploying our own platform allowed us to modulate a lot of the visualization construction in a way Tableau could not. Each dashboard is composed of standardized charts and graphs and represented on a different website page (Fig. C8-C17). Standardizing chart design limited each dashboard to just a few charts that were capable of showing any aggregate information and significantly sped up dashboard construction.

In total, Riverside County is made up of five Supervisory Districts that are further broken down into 26 city boundaries. Additionally, the dashboards account for five "Unincorporated Areas" that fall within a supervisory district but not within any labeled city boundary. Prior to RCHI, Riverside County did not provide graphical visualizations outside of tables for data on the individual city level. Representation of such data was an important goal for the county because localized programs could only be given data in the raw format and had to devote their own resources into creating graphics. To address this problem, the map and city level dashboards include a location-based filter to represent data within selected boundaries. Riverside is represented three times within the filter because its boundary uniquely falls into Supervisorial District one and two. Therefore, Riverside counts are represented as data points that fall only within the Supervisorial District one, two, or both boundaries respectively. The technical process of visualization is not discussed in this report.

Methodology Summary

From 2019 to 2020, the methodology for streamlining the Point-In-Time count has evolved with better optimizations, accuracies, and data visualizations. Despite this, the idea behind the dataflow pipeline (Fig. 2) has largely remained the same. In 2019, Tableau handled the data hosting, allowing for easier visualization, however, steps like deduping, counting and data checking still required time-consuming manual interaction (Fig. 6). Unfortunately, once the team realized the visualizations could not be made compatible with next year's data, the methodology had to be augmented to work with an open-source website (Fig. 7). By the 2020 PIT count, most of the data cleaning processes as well as the dashboards themselves were not only automated but backward compatible with data from the previous year.

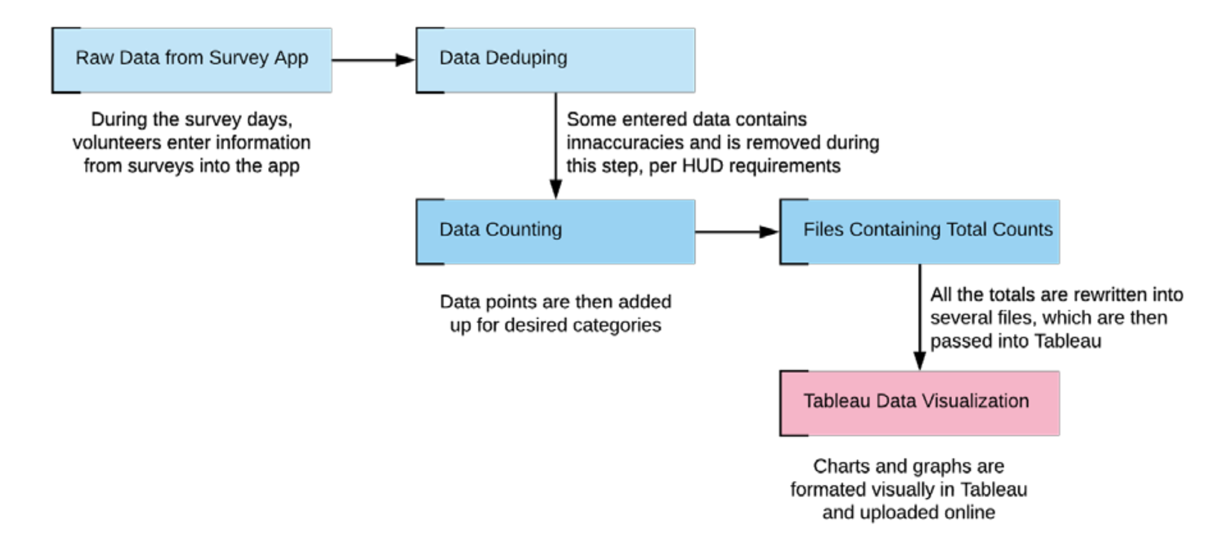


Fig. 6, Detailed 2019 Dataflow Pipeline

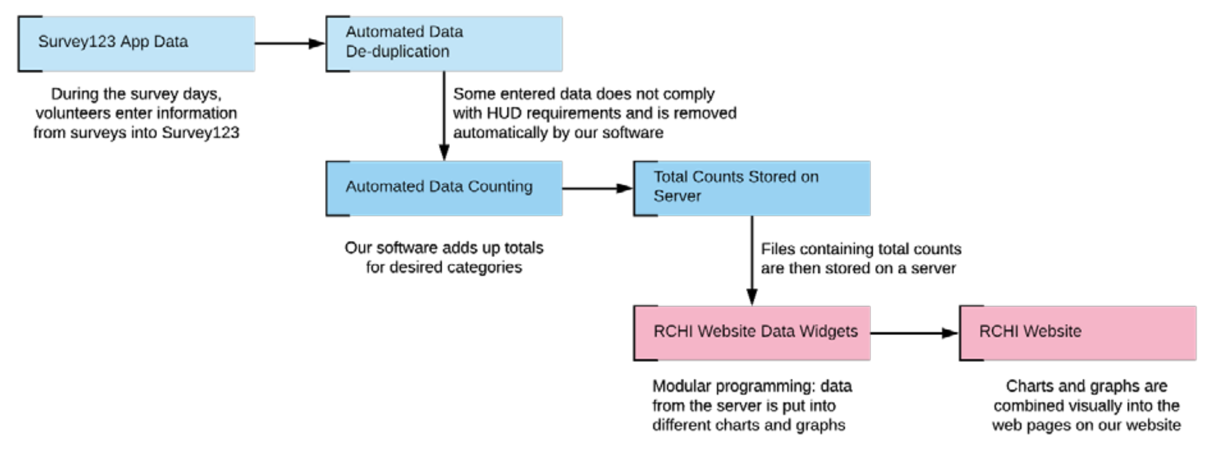


Fig. 7, Detailed 2020 Dataflow Pipeline

Results

This section analyzes the success of the project in improving the efficiency, accuracy, and visual representation of the Point-In-Time Count data. Success is determined by examining the improvements to Point-In-Time Count methodology as well as comparing statistical data related to the counts.

Improvements in Survey Efficiency and Accuracy

Changes To Surveying Methods

Although UCR's team was not responsible for the decision to switch from paper surveys to the Survey 1-2-3 app, this project utilized the new metadata recorded by the survey app to ensure a higher level of accuracy for the PIT count.

Temporal Metadata

Each data point contained a timestamp with the exact date and time it was created. HUD standards mandate surveys that start before 5:00am on the initial day of the count and after 5:00pm seven days later are invalid. For prior years, completed surveys were assumed valid with 0 surveys removed, now survey removal due to invalid survey time is enforced.

Spatial Metadata

Each data point contained GPS coordinates of the survey location collected using in-app Esri GIS mapping software. For prior years, survey locations were self-reported by volunteers writing down the nearest cross streets to where the survey took place. In 2018, there was no mention of surveys removed due to an invalid location. In 2019, GPS data confirmed 2 surveys occurred outside the county boundary while for 2020 the number increased to 8. This suggests that surveys could occur outside Riverside County however prior to 2019, this was not checked.

Spatially, the **City of Riverside** is unique because its boundary falls into two separate Supervisory Districts, Supervisory Districts 1 and 2. For such cases, HUD recommends evenly splitting the population between the districts. With exact GPS coordinate data, we were able to determine a more accurate split, with the exact distributions listed below (Fig. 8).

	2018		2019		2020	
Supervirosial District 1	184	50.27%	238	54.21%	341	58.09%
Supervisorial District 2	182	49.73%	201	45.79%	246	41.91%
Total Riverside Population	366	100%	439	100%	587	100%

Fig. 8, Population Size of Unsheltered Homeless Individuals In City of Riverside By Supervisorial District

Additionally, a total of 9 **Unassigned Surveys** were included in the 2018 count that could not be definitely placed into a certain city due to incomplete information. Exact GPS location ensured no survey was unassigned for the 2019 and 2020 counts and ultimately contributed to a more accurate count.

Automation of Data Cleaning Process

In 2018, paper surveys were manually inputted into a Microsoft Access system by 5 Point-In-Time count team members, where the data was subsequently deduplicated and counted. Manual input risks human error and was avoided by automating the process in the subsequent two years. By the 2020 Point-In-Time Count, much of the data cleaning process had been combined and manual data transfer occurred only between the cleaning and the data visualization process. Manual data manipulation occurred only once as well when determining the validity of self-identified living situations.

Data Deduplication

Automating data deduplication was a key optimization factor between the 2019 and 2020 count. Manually identifying duplicate data entries by comparing 6 characteristics was tedious and error-prone. For the 2020 PIT count, a data cleaning script identified all duplicates very efficiently in only a few seconds. These duplicates were still manually checked by the team to ensure accuracy of the code and it was determined the program was able to successfully locate and remove every duplicate survey. Next year, deduplication will be even more efficient since high confidence in the code suggests manual checking of duplicates would no longer be required.

Removal Logs

Removal Log creation was significantly improved between 2019 and 2020 counts. In 2019, invalid data was manually removed from the dataset and then it's information and reason for removal had to be manually added to the remove log. The 2020 Data Cleaning and Deduplication script automatically logged data for each removal category and produced a master remove log containing all the removed data points and the invalidating column's contents as proof (Fig. 9).

ObjectID	GlobalID	Reason	Note
****	****	Records where CreationDate < 01/29/2019 5:00:00 AM removed.	
****	****	Records where Living Situation equals other AND Living Situation Other is not homeless.	says moms house
****	****	Duplicate removed.	

GlobalID	UniqueID	Action	Proof
****	****	Invalid Survey Date	2020-01-13 20:50:37
****	****	Duplicate Record	First Initial, Last Initial, Age, Ethnicity, Gender, Veteran Status
****	****	Living Situation Other HMIS	Sober liv house
****	****	Living Situation Other And Not Homeless	hotel

Fig. 9, Comparison of Remove Log Formats From 2019 (top) to 2020 (bottom)

Automated compilation of the remove log ensured the removed data was represented accurately and removed for valid reasons.

Data Counting

Certain data elements that depended on specific answers to multiple survey questions, such as “Disabling Condition” and “Chronically Homeless” were more accurately calculated during the run time of the aggregating step process (Appendix A3, A4). The specific condition for “Chronically Homeless” that needed additional data in the household group counted as “Chronically Homeless” as well and required complex data manipulation achievable with the Python Pandas library for an accurate count.

Increase of Visual Representation

Prior to 2019, Riverside County annually produced a single infographic containing visual summarizations of the results from the PIT count (Fig. B2). Several additional visual representations were included in the official report, however, there was no centralized system in place for visually presenting Point-In-Time data.

Increase in Information Presented

To address this issue, multiple dashboards were created to visually present the demographic, subpopulation, and trend data of the Point-In-Time Data. Representation of trend data experienced the most significant increase of 1400% because 5-year trends were added for multiple subpopulation categories compared to a single 5-year trend graph shown in the years prior to 2019.

2019 Tableau Dashboards

Seven unique dashboards were created (Fig. C1-C7). The dashboards are dynamic, with hoover and filter capabilities and can be further explored at this link.

(https://sites.google.com/ucr.edu/paea-lependu/rchi/pit-2019)

The Supervisory Districts dashboard was split into 5 Supervisory Districts while the City Level Information dashboard utilized a location-based filter to represent data specific to selected locations, creating a total of 43 dashboards that represented visually unique information on the Point-In-Time Count (Fig. B4).

2020 Open Source Website Dashboards

Ten unique dashboards were created (Fig. C8-C17) representing a 42% increase of unique dashboards available to the prior year. The dashboards are dynamic, with hoover and filter capabilities, and can be further explored at this link.

(http://rchi.cs.ucr.edu/)

Additionally, a new Map dashboard was added that allowed users to view location-specific data by interacting with a map (Fig. C17). Similarly to 2019, the Supervisory District dashboard was split into 5 separate dashboards while both the map and City Level Information dashboards utilized a location filter. In total, there are 78 dashboards containing uniquely presented information representing an 81% increase from the previous year (Fig. B5).

Increased Subpopulation Representation

From 2019 to 2020, two dashboards were created for at-risk unsheltered subpopulation groups whose data is commonly referenced by organizations when applying for grants and determining funding allocation. The Newly Homeless dashboard shows detailed subpopulation and demographic information for individuals experiencing homelessness for the first time in 12 months (Fig. C10). Similarly, the Seniors dashboard shows subpopulation and demographic information for Adults ages 60 and up (Fig. C11).

In 2020, a new survey question was added that tracked if a homeless individual is a pet owner. The 280 individuals that own pets are represented in multiple dashboards and correlation statistics will be available on it in the upcoming years

Diversification of Charts and Graphs

In 2018, there were a total of 28 provided charts and graphs on the data with the majority of them (68%) being tables. Undeniably informative, tables do not visualize information in a way that is intuitive to the human eye. To combat this, the project succeeded in increasing the total number and variety of charts and graph visualizations of PIT Count data each year (Fig.10).

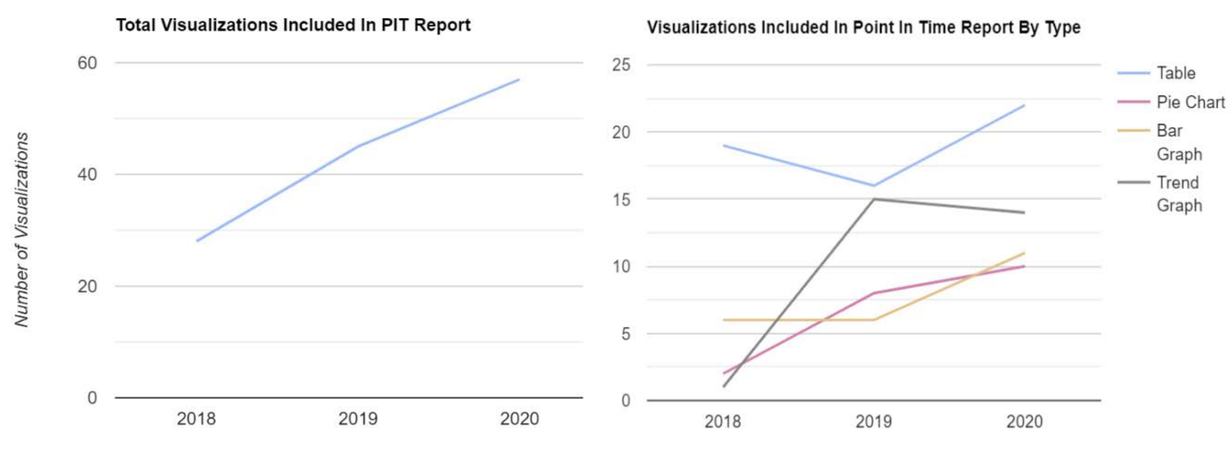


Fig. 10, Total Graph Visualizations (left) and Graph Variety(right) From 2018-2020

By 2020, the dashboards contained a total of 57 charts that represented a 103.57% increase from the start of the project. Out of the 57 charts, only 39% were in table format, suggesting a successful diversification of data visualization tools. The full breakdown of chart diversification by year is available below and in large format in the appendix (Fig. B7).

Dashboards/Chart Types	Table	Pie Chart	Bar Graph	Trend Graph	**Total Charts**
2018 PIT Count Data Visualizations					
2018 PIT Report	16	1	4	0	
2018 PIT Count Fact Sheet	3	1	2	1	
Total	**19**	**2**	**6**	**1**	**28**
2019 PIT Count Dashboards					
General Sheltered & Unsheltered Information	4	4	1	1	
Sheltered vs Unsheltered	3	1	2	1	
Supervisorial District Dashboards	4	2	1	1	
Unsheltered Subpopulation Trends [1-3]	0	0	0	12	
City-Level Information	5	1	2	0	
Total	**16**	**8**	**6**	**15**	**45**
% Increase From 2018	-15.79%	300%	0%	1400%	60.71%
2019 PIT Count Dashboards					
General Sheltered & Unsheltered Information	4	3	1	1	
Sheltered vs Unsheltered	4	0	2	1	
Supervisorial District Dashboards	4	2	1	1	
Unsheltered Subpopulation Trends [1-3]	0	0	1	11	
City-Level Information	3	1	2	0	
Newly Homeless	4	2	1	0	
Seniors 60+	3	2	1	0	
Map Dashboard	0	0	2	0	
Total	**22**	**10**	**11**	**14**	**57**
% Increase From 2018	15.79%	400%	83.33%	1300%	103.57%
% Increase From 2019	37.50%	25%	83.33%	-6.67%	26.67%

Annually Reusable Code

The project's most important optimization goal was to create a single data pipeline that could be applied to subsequent years with minimal change to the code. Assuming the raw data format and table names stay consistent, this goal has been largely achieved by the publication of the 2020 Point-In-Time count. The data processing, which includes data cleaning, duduping, and counting has been successfully tested on the 2019 and 2020 PIT count dataset with no necessary changes to the code. Once aggregated, any year's data could be uploaded to the backend server and successfully visualized on the RCHI website within a matter of minutes.

Conclusion and Implications

The analysis within this paper concludes that over the last two years, the Point-In-Time count has been significantly optimised by UCR's team with respect to the accuracy, efficiency, and data visualization. Unsheltered survey data processing has evolved from a series of manual steps that had to be repeated annually in 2018 to a single, almost autonomous process by the 2020 count. Data visualization improved from an infographic to 10 centralized and unique dashboards that contain in-depth, graphical information on the aggregate data of the count. The availability of data visualizations has increased by over 100% from 2018.

Successful tests run with new data gathered in the upcoming years will further help automate the data pipeline process as confidence in the code will grow and less manual checking will be required. In the next few years, it is highly possible the entire data pipeline from raw data to data visualization will become fully autonomous for Riverside County. This implies that the timeline for visualizing the Point-In-Time Count could decrease from several months to a matter of minutes and allow Riverside County to dedicate more time and resources to helping the homeless population in hands on ways.

Riverside County is just one of over 3,000 counties mandated to do the annual Point-In-Time Count by the federal government. Being a larger county, Riverside has a lot of resources for analysis and informed policymaking decisions than many of the smaller counties nearby. The automated data analysis platform created by this project does not require significant resources to report on the annual count. In the future, other counties could work with UCR to standardize their raw Point-In-Time Count data in a format similar to Riverside County's and this project would be able to analyze it for them. This project is already noticed by other counties, like Yorba Linda, who is in the process of seeing if similar collaboration could work for them.

It is undeniable that homelessness is an unfortunate and prominent issue in many counties within California. Knowing the statistical makeup of the homeless population is a vital first step required for informed policy making and funding allocation that can successfully lower the number of people living on the street. This project was created to simplify that first step and ultimately create more time for direct involvement with the homeless population. In its first two years, it has shown promise in redirecting the resources of the Point-In-Time Count from the data and back to the people, it is counting.

Appendix A

Key Terms

A1. **HUD 6 Recommended Categories For Identifying Duplicate Data**

1. First Initial
2. Last Initial
3. Age
4. Veteran Status
5. Ethnicity
6. Race

A2. **Unsheltered Homeless Individual**

An individual with:

a primary nighttime residence that is a public or private place not designed for or ordinarily used as a regular sleeping accommodation for human beings, including a car, park, abandoned building, bus or train station, airport, or camping ground

A3. **Chronically Homeless Person**

A person who:

A. Is homeless and lives in a place not meant for human habitation, a safe haven, or in an emergency shelter; and

B. Has been homeless and living or residing in a place not meant for human habitation, a safe haven, or in an emergency shelter continuously for at least 1 year or on at least four separate occasions in the last 3 years where the combined length of time homeless in those occasions is at least 12 months; and

C. Has a disability.

When a household with one or more members includes an adult or minor head of household who qualifies as chronically homeless, then all members of that household should be counted as a chronically homeless person in the applicable household type table. For example, if one adult in a two adult household is identified as chronically homeless, both adults should be counted as a chronically homeless person in the households without children category of the PIT count.

A4. **Homeless Persons with Developmental Disability**

An individual with one or more of the following conditions:

A. A physical, mental, or emotional impairment, including an impairment caused by alcohol or drug abuse, post-traumatic stress disorder, or brain injury that:

(1) Is expected to be long-continuing or of indefinite duration

(2) Substantially impedes the individual's ability to live independently and;

(3) Could be improved by the provision of more suitable housing conditions.

B. A developmental disability, as defined in section 102 of the Developmental Disabilities Assistance and Bill of Rights Act of 2000 (42 U.S.C. 15002); or

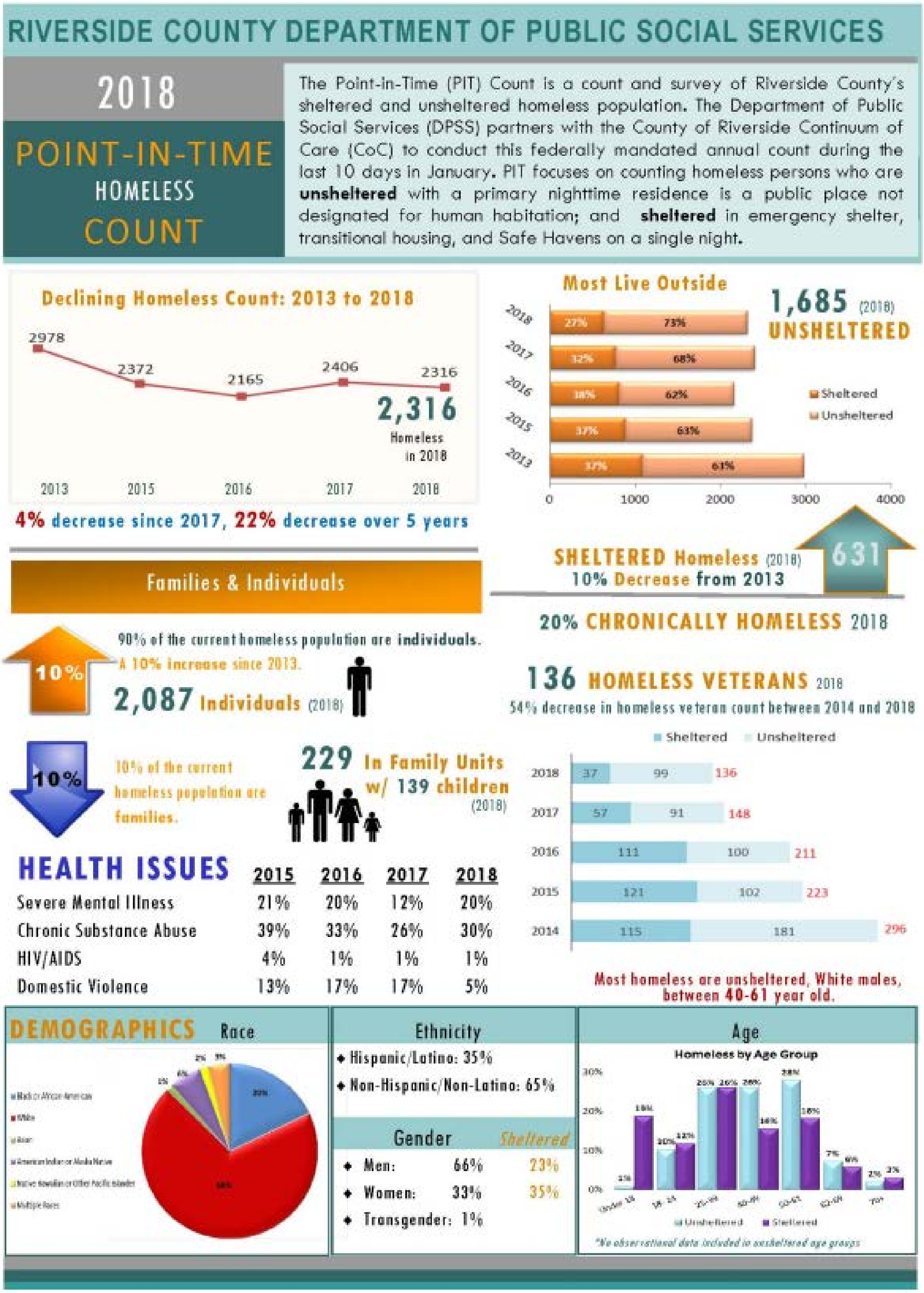
C. The disease of acquired immunodeficiency syndrome (AIDS) or any condition arising from the etiologic agency for acquired immunodeficiency syndrome (HIV).

Appendix B

Visual Graphics Referenced Throughout Report

Category	Responce Options
Demographic Information	
Race	American Indian, Asian, Black, Native Hawaiian, White, Multiple Races
Ethnicity	Hispanic, Non Hispanic
Gender	Male, Female, Transgender, Gender Non-Conforming
Age (Observational)	Children(<18), Youth(18-24), Adults(25+)
Age (Interview)	Self-Identified Age
Living Situation	Street, Encampment, Vehicle, Park, Abandoned Building, Under Bridge, Bus, Other (could be self-identified)
Household Composition	Adults Only, Children Only, Adults and Children
Subpopulation Information *Interview Survey Only*	
Veterans	Yes/No
Chronically Homeless	Yes/No
First Time Homeless	Yes/No
Substance Abuse	Yes/No
Victims of Domestic Violence	Yes/No
Incarcerated Within The Last 12 Months	Yes/No
HIV/AIDS	Yes/No
Mental Health Conditions	Yes/No
Suffering from PTSD	Yes/No
Suffering from Brain Injury	Yes/No
Developmental Disability	Yes/No
Physical Disability	Yes/No
Pet Owner	Yes/No

Fig. B1, List of all PIT survey information used by PIT Dashboards. Response options are preset responses that a volunteer filling out the survey could choose. In addition to the given response options, each category has an “Unknown/Unsure” response option. “Self-Identified” categories represent a manually imputed answer into the app.



HEALTH ISSUES	2015	2016	2017	2018
Severe Mental Illness	21%	20%	12%	20%
Chronic Substance Abuse	39%	33%	26%	30%
HIV/AIDS	4%	1%	1%	1%
Domestic Violence	13%	17%	17%	5%

Fig. B2, Infographic of aggregate 2018 Point-In-Time Count data represented through charts and graphs. The material within this infographic is what initial dashboard designs were based on (2018 Point In Time Count)

Individual Remove Logs	Number Flagged
Invalid Survey Date/Time	165
Invalid Survey Location	8
Already Surveyed	0
Unknown Living Situation	0
Incomplete Interview Information	275
Incomplete Observational Information	91
Duplicate Entry of Same Persons	76
Check Log	**Number Flagged**
Living Situation Other	94
Total Data Points Flagged	**709**

Fig. B3, 2020 PIT Individual Remove Logs Statistical Summary

Unique Dashboard	Location Filtering
General Sheltered & Unsheltered Information	
Sheltered vs Unsheltered	
Supervisorial District Dashboards	Supervisorial District 1
	Supervisorial District 2
	Supervisorial District 3
	Supervisorial District 4
	Supervisorial District 5
Unsheltered Subpopulation Trends [1]	
Unsheltered Subpopulation Trends [1]	
Unsheltered Subpopulation Trends [1]	

Unique Dashboard	Location Filtering		
City-Level Information	Banning	Jurupa Valley	Riverside Supervisory District 1
	Beumont	La Quinta	Riverside Supervisory District 2
	Blythe	Lake Elisnore	Riverside Supervisory District 1&2
	Calimesa	Menifee	San Jacinto
	Cathedral City	Moreno Valley	Temecula
	Coachella	Murrieta	Wildomar
	Corona	Norco	Unincorporated Area 1
	Desert Hot Springs	Palm Desert	Unincorporated Area 2
	Hemet	Palm Springs	Unincorporated Area 3
	Indian Wells	Perris	Unincorporated Area 4
	Indio	Rancho Mirage	Unincorporated Area 5

Fig. B4, 2019 List of 7 Unique and 43 Total Dashboards By Name

Unique Dashboard	Location Filtering
General Sheltered & Unsheltered Information	
Sheltered vs Unsheltered	
Newely Homeless	
Seniors	
Supervisorial District Dashboards	Supervisorial District 1
	Supervisorial District 2
	Supervisorial District 3
	Supervisorial District 4
	Supervisorial District 5
Unsheltered Subpopulation Trends [1]	
Unsheltered Subpopulation Trends [1]	
Unsheltered Subpopulation Trends [1]	

Unique Dashboard	Location Filtering		
City-Level Information	Banning	Jurupa Valley	Riverside Supervisory District 1
	Beumont	La Quinta	Riverside Supervisory District 2
	Blythe	Lake Elisnore	Riverside Supervisory District 1&2
	Calimesa	Menifee	San Jacinto
	Cathedral City	Moreno Valley	Temecula
	Coachella	Murrieta	Wildomar
	Corona	Norco	Unincorporated Area 1
	Desert Hot Springs	Palm Desert	Unincorporated Area 2
	Hemet	Palm Springs	Unincorporated Area 3
	Indian Wells	Perris	Unincorporated Area 4
	Indio	Rancho Mirage	Unincorporated Area 5
Map Dashboard	Banning	Jurupa Valley	Riverside Supervisory District 1
	Beumont	La Quinta	Riverside Supervisory District 2
	Blythe	Lake Elisnore	Riverside Supervisory District 1&2
	Calimesa	Menifee	San Jacinto
	Cathedral City	Moreno Valley	Temecula
	Coachella	Murrieta	Wildomar
	Corona	Norco	Unincorporated Area 1
	Desert Hot Springs	Palm Desert	Unincorporated Area 2
	Hemet	Palm Springs	Unincorporated Area 3
	Indian Wells	Perris	Unincorporated Area 4
	Indio	Rancho Mirage	Unincorporated Area 5

Fig. B5, 2020 List of 10 Unique and 78 Total Dashboards By Name

Total Survey Count Returned	Rejected Survey Count (Not Entered)	New Sub Total	Rejected Surveys (Duplicates)	Final Count (total number of people)
1,797 (1,186 interview, 189 youth surveys, 422 observational)	**98** (33 interview, 18 youth, 47 observational)	**1699** (1153 interview, 171 youth surveys, 375 observational)	**14** (11 interview, 3 youth, 0 observational)	**1685** (1142 interview, 168 youth surveys, 375 observational)

Fig. B6, 2018 Breakdown of PIT Count Survey Data Cleaning and Deduplication (2018 Point In Time Survey)

Dashboards/Chart Types	Table	Pie Chart	Bar Graph	Trend Graph	**Total Charts**
2018 PIT Count Data Visualizations					
2018 PIT Report	16	1	4	0	
2018 PIT Count Fact Sheet	3	1	2	1	
Total	**19**	**2**	**6**	**1**	**28**
2019 PIT Count Dashboards					
General Sheltered & Unsheltered Information	4	4	1	1	
Sheltered vs Unsheltered	3	1	2	1	
Supervisorial District Dashboards	4	2	1	1	
Unsheltered Subpopulation Trends [1-3]	0	0	0	12	
City-Level Information	5	1	2	0	
Total	**16**	**8**	**6**	**15**	**45**
% Increase From 2018	-15.79%	300%	0%	1400%	60.71%
2019 PIT Count Dashboards					
General Sheltered & Unsheltered Information	4	3	1	1	
Sheltered vs Unsheltered	4	0	2	1	
Supervisorial District Dashboards	4	2	1	1	
Unsheltered Subpopulation Trends [1-3]	0	0	1	11	
City-Level Information	3	1	2	0	
Newly Homeless	4	2	1	0	
Seniors 60+	3	2	1	0	
Map Dashboard	0	0	2	0	
Total	**22**	**10**	**11**	**14**	**57**
% Increase From 2018	15.79%	400%	83.33%	1300%	103.57%
% Increase From 2019	37.50%	25%	83.33%	-6.67%	26.67%

Fig. B7 Breakdown of Chart Visualizations By Year

COUNTY OF RIVERSIDE
Department of Public Social Services
CoC - CORE Region

THE Point-In-Time Count Survey

Start Here

Respond online today at:
https://arcg.is/10OGTX

This form asks for information about people who are living or staying in a place not meant for human habitation.

LOCATION

CITY ZIP

ADDRESS

X Y

If you need help or have questions about completing this form, please call 1-951-358-3844.

For more information about the Point-In-Time Count Survey, visit our web site at: https://rivcoexchange.com.

FORM **PITCS-1(FINAL)(2019)**
(12-03-2018)

Please print today's date and time.

Month Day Year : AM/PM

Please print the name of the person who is filling out this form. We will only contact you if needed for offical business.

Last Name (Please print) First Name MI

Are you able to survey this person?

- ☐ Yes → Continue with survey.
- ☐ No → Go to observation tool on page 5.

Hello, my name is ________________. Today we are conducting a survey to better understand a person's housing status. It is up to you whether you want to participate, and your answers will not be shared with anyone outside of our team. For your assistance, we have an incentive bag with goodies after you complete the survey. **Can I have about 10 minutes of your time?**

- ☐ Yes → Continue with survey.
- ☐ No → Thank respondent and go to observation tool on page 5.

1 Where did you sleep on the night of Monday, January 28, 2019?

- ☐ Street of sidewalk
- ☐ Under bridge/overpass
- ☐ Park
  Specify
- ☐ Abandoned building
- ☐ Bus, train station, airport
- ☐ Vehicle (car, van, RV, truck)
  Specify
  - ☐ Car
  - ☐ Van
  - ☐ Truck
  - ☐ Camper
  - ☐ RV (Recreational Vehicle) in which occupants do not have access to sewer, water, and electricity connections and/or in disrepair (e.g., holes, broken windows, flat tires, removed or broken siding)
  - ☐ RV (Recreational Vehicle) with access to sewer, water, and electricity connections and not in disrepair → STOP the survey.
- ☐ Emergency shelter (or Motel/Hotel paid for by a non-profit or government entity)
- ☐ Transitional housing
- ☐ Motel/hotel that you paid for → STOP the survey.
- ☐ House or apartment → STOP the survey.
- ☐ Jail, hospital, treatment program → STOP the survey.
- ☐ Other location
  Specify

A Answer questions 2 if EMERGENCY SHELTER or TRANSITIONAL HOUSING; otherwise, SKIP to question 3.

2 What is the name of the shelter/program?

3 Did another volunteer already ask you these same questions about where you stayed last night?

- ☐ Yes → STOP the survey.
- ☐ No → Continue with survey.

4 Do you have a spouse or partner who is also homeless and living with you? A partner is a person you live with and share a common family life but are not joined in a traditional marriage.

- ☐ Yes
- ☐ No

5 a. Do you have children under the age of 18 who are homeless and living with you today?

- ☐ Yes
- ☐ No

b. If YES, how many children are living with you today?

➔ Please ask the following questions to each family member living in a place not meant for human habitation.

Interview

6 a. What is the first initial of your FIRST name?

If respondents does not know, refused, or does respond, write out 'Doesn't know/Refused'.

FI

b. What is the first initial of your LAST name?

If respondents does not know, refused, or does respond, write out 'Doesn't know/Refused'.

LI

7 How is this person related to Person 1?

If Person 1, select 'Self'.

- ☐ Self
- ☐ Spouse or partner
- ☐ Unreleated household member
- ☐ Child
- ☐ Other relative
- ☐ Doesn't know/ Refused

8 How old are you?

Age (in years)

9 Are you Hispanic or Latino?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

10 What is your race?

- ☐ American Indian or Alaska Native
- ☐ Asian
- ☐ Black or African American
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ White
- ☐ Multiple Races
- ☐ Doesn't know/ Refused

11 How would you define your gender?

- ☐ Female
- ☐ Male
- ☐ Trans Female (MTF or Male to Female)
- ☐ Trans Male (FTM or Female to Male)
- ☐ Gender non-conforming (i.e. not exclusively male or female)
- ☐ Doesn't know/ Refused

12 a. What CITY were you born in? b. What STATE were you born in?

13 Did you become homeless for the first time during the past 12 months?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

14 Have you been living in a shelter and/or on the streets, in abandoned buildings, or vehicle for the past year or more?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

15 a. Have you been living in a shelter and/or on the streets, in abandoned buildings, or vehicle at least 4 separate times during the last 3 years including now?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. If YES, was combined length of time 12 months or more?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

16 Why did you become homeless? You can select one or more reasons.

- ☐ Unemployment
- ☐ Lack of income for housing
- ☐ Discharged from medical institution
- ☐ Discharged from jail or prison
- ☐ Mental illness
- ☐ Runaway/left home
- ☐ Other - Specify
- ☐ Doesn't know/ Refused

C Answer questions 16-24 if respondent is UNDER AGE 25. Otherwise, SKIP to to the questions for ADULTS on page 4.

Youth (Under 25)

16 - 24 PERSONS UNDER AGE 25. Ask these questions to respondents under age 25 who are present or sleeping in the same place.

16 **a. FEMALE. Are you currently pregnant?**

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. MALE. Are you expecting to become a parent in the next 9 months?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

17 **a. Have you ever been placed in a foster care or stayed in a group home?**

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. If you left [SETTING] in the past 3 years, did anyone help you get housing?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

18 **a. Have you stayed overnight or longer in jail, prison, or juvenile detention facility?**

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. If you left [SETTING] in the past 3 years, did anyone help you get housing?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

19 **a. Have you stayed overnight or longer in a treatment or healthcare facility?**

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. If you left [SETTING] in the past 3 years, did anyone help you get housing?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

20 **Are you currently enrolled in school?**

- ☐ Attending school regularly
- ☐ Attending school irregularly
- ☐ Graduated from high school
- ☐ Obtained GED
- ☐ Dropped out
- ☐ Suspended
- ☐ Expelled
- ☐ Doesn't know/ Refused

21 **What is the highest grade or level of schooling you completed?**

- ☐ Less than grade 5
- ☐ Grades 5-6
- ☐ Grades 7-8
- ☐ Grades 9-11
- ☐ Grade 12
- ☐ School program does not have grade levels
- ☐ GED
- ☐ Some college
- ☐ Associate's degree
- ☐ Bachelor's degree
- ☐ Graduate degree
- ☐ Vocational certification
- ☐ Doesn't know/ Refused

22 **In the past year, in what ways did you make money?**
You can select one or more options.

- ☐ Full-time job
- ☐ Part-time job including on-call or irregular hours
- ☐ Seasonal/ sporadic (including day labor)
- ☐ Working under the table
- ☐ Money from friends or family
- ☐ Hustling
- ☐ Other Specify ______
- ☐ Sex work
- ☐ Government program (disability, welfare, food stamps, unemployment, etc.)
- ☐ Panhandling
- ☐ Doesn't know/ Refused

23 **a. Think about the last time you felt that you were living in stable housing, or housing where you felt safe. How long ago was that?**

- ☐ Less than 1 month ago
- ☐ 1 month to less than 3 months ago
- ☐ 3 months to less than 6 months ago
- ☐ 6 months to 1 year
- ☐ More than 1 year
- ☐ Never felt stably housed — SKIP to question 24.
- ☐ Doesn't know/ Refused

b. What is the primary reason you left or lost your last stable housing situation?

- ☐ Chose to leave
- ☐ Had to leave
- ☐ Doesn't know/ Refused

24 **In the past year, what services or supports, for example from government programs or charities have you accessed?**
You can select one or more options.

- ☐ Free meals
- ☐ Transportation assistance or bus passes
- ☐ Job training or employment services
- ☐ Drop-in/ day services
- ☐ Health services
- ☐ Mental health services
- ☐ Other Specify ______
- ☐ Housing services
- ☐ Education services
- ☐ Substance abuse treatment/ services
- ☐ Legal assistance
- ☐ None
- ☐ Doesn't know/ Refused

Adult (18+)

25-36 PERSON AGE 18 AND OLDER. *Ask these question to respondents age 18 and older who are present or sleeping in the same place.*

25 a. Have you ever served on active duty in the U.S. Armed Forces, Reserves, or National Guard?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. When did you serve on active duty in the U.S. Armed Force? Mark a box for EACH period in which this person served, even if just for part of the period.

- ☐ September 2001 or later
- ☐ August 1990 to August 2001 (including Persian Gulf War)
- ☐ May 1975 to July 1990
- ☐ Vietnam era (August 1964 to April 1975)
- ☐ February 1955 to July 1964
- ☐ Korean War (July 1950 to January 1955)
- ☐ January 1947 to June 1950)
- ☐ World War II (December 1941 to December 1946)
- ☐ November 1942 or earlier
- ☐ Doesn't know/ Refused

The next set of questions asks about sensitive topics. You don't have to answer any question that you don't want to. However, your answers will be combined with the answers of other people who take the survey. The results will help provide better programs and services to homeless people.

26 a. Were you recently released from jail or prison?

- ☐ Yes, within 90 days or less
- ☐ Yes, in the past 12 months
- ☐ No

b. If YES, were you released on probation or parole?

- ☐ Probation
- ☐ Parole
- ☐ Completed Sentence

27 Do you have a long-lasting physical disability that makes it difficult for you to live independently?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

28 Do you have a long-lasting developmental disability that makes it difficult for you to live independently?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

29 Do you have a serious mental illness or emotional impairment that seriously limits your ability to live independently?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

30 Do you have a substance use disorder that is ongoing and makes it difficult for you to live independently?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

31 Do you have AIDS or an HIV-related illness?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

32 a. Do you have Post-Traumatic Stress Disorder or PTSD?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. If YES, does it keep you from holding a job or living in stable housing?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

33 a. Have you ever had a serious injury to your brain?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

b. If YES, does it keep you from holding a job or living in stable housing?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

34 Do you receive any disability benefits such as Social Security Income, Social Security Disability Income, or Veteran's Disability Benefits?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

35 How much is your monthly income?

- ☐ No income
- ☐ $1 to $250
- ☐ $251 to $500
- ☐ $501 to $1000
- ☐ More than $1000
- ☐ Doesn't know/ Refused

36 Are you experiencing homelessness because you are currently fleeing domestic violence, dating violence, sexual assault, or stalking?

- ☐ Yes
- ☐ No
- ☐ Doesn't know/ Refused

Those are all the question we have for you. We realize that some of the topics covered are personal and can be difficult to talk about. As a reminder your responses will not be shared with anyone outside of our team. Thank you for taking the survey!

Observation

Complete this form only if you are unable to complete an interview survey.

1. **Please indicate why you are using the observation tool:**
   - ☐ You are unable to enter a site
   - ☐ You cannot conduct a PIT count survey (person refused to answer questions, language or other problems)
   - ☐ You do not wish to disturb people sleeping

2. **Total persons staying together as household:**
   (Use separate observation forms for each household)

Adults	Children	Not sure if Adult/Child	Total

3. **Location where observed**
   - Example: northwest corner of 1st Avenue and Main Street

4. **Is this person homeless? How certain are you that the person meets HUD's criteria of staying in a place not meant for human habitation (e.g., tent, vehicle, park bench, etc.)?**
   - ☐ Definitely
   - ☐ Possibly
   - ☐ Not sure

5. **What is this person's age?**
   - ☐ Under 18
   - ☐ 18-24
   - ☐ 25+
   - ☐ Not sure

6. **What is this person's gender?**
   - ☐ Male
   - ☐ Female
   - ☐ Not sure

7. **What is the person's race ?**
   - ☐ American Indian or Alaska Native
   - ☐ Asian
   - ☐ Black or African American
   - ☐ Native Hawaiian or Other Pacific Islander
   - ☐ White
   - ☐ Multiple Races
   - ☐ Not sure

8. **What is the person's ethnicity?**
   - ☐ Non-Hispanic/Non-Latino
   - ☐ Hispanic/Latino
   - ☐ Not sure

9. **Other information or identifying characteristics. If possible, please include:**
   - Clothing (hats, accessories, any military or other emblems)
   - Other physical characteristics or conditions like tattoos, scars, braces, casts, etc.

Return Instructions

Please make sure you have...

- listed your name and answered the questions on page 1
- indicated the location of where the survey was conducted
- answered all Interview, Youth, and Adult questions for each person.

Then...

- please ensure the questionnaire is returned to the Site Coordinator OR:

  Laura Gonzalez-Rivera
  PIT Coordinator
  1111 Spruce Street
  Riverside, CA 92507

Thank you for participating in the Point-In-Time Count.

For CoC - CORE Region Use

POP EDIT PHONE QA1 QA2

EDIT CLERK TELEPHONE CLERK QA3 QA4

The CoC- CORE Region estimates that, for the average interview, this form will take 10 to 15 minutes to complete, including the time for reviewing the instructions and answers. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to: 1111 Spruce Street Riverside, CA 92507. You may e-mail comments to RivCoPIT@RivCo.org; use "Point-In-Time Count Survey" as the subject.

Respondents are not required to respond to any information collection.

Form **PITCS-1(FINAL)(2019)** (12-03-2018)

Fig. B8, 2019 PIT Count Survey Instrument (nearly identical to 2020 survey instrument)

Appendix C

Point-In-Time Count Final Dashboards

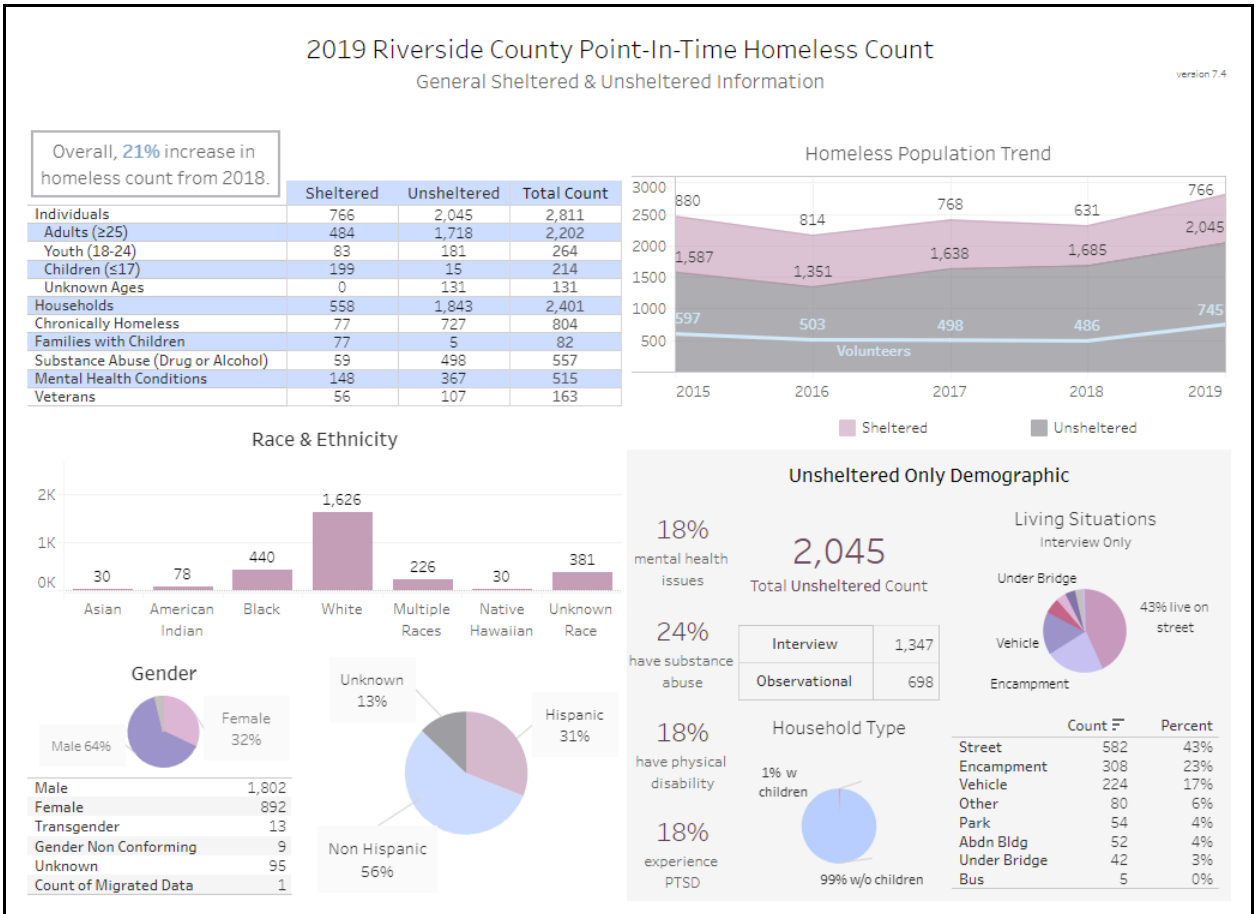
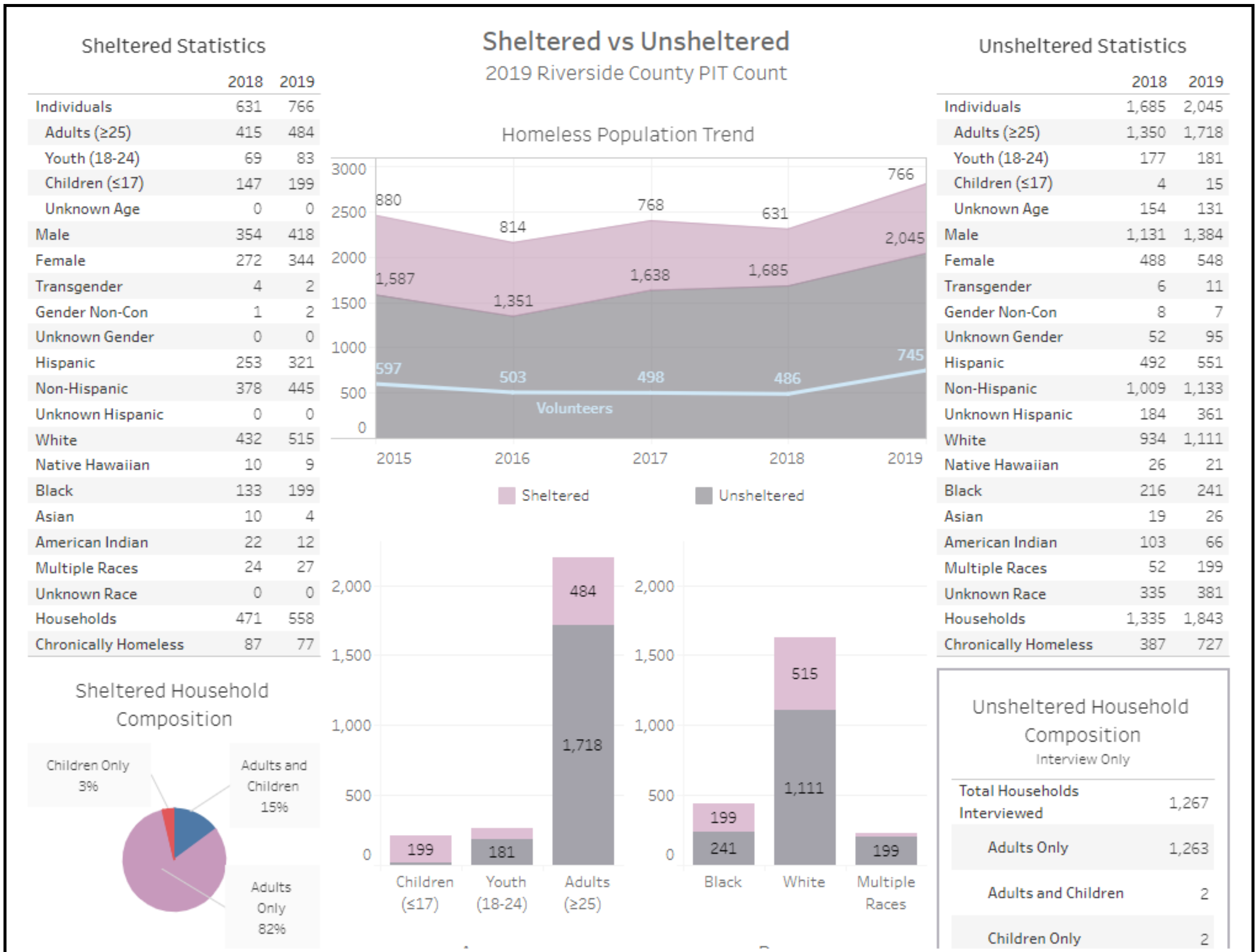


Fig. C1 2019 General Sheltered & Unsheltered Tableau Dashboard



Sheltered Statistics

	2018	2019
Individuals	631	766
Adults (≥25)	415	484
Youth (18-24)	69	83
Children (≤17)	147	199
Unknown Age	0	0
Male	354	418
Female	272	344
Transgender	4	2
Gender Non-Con	1	2
Unknown Gender	0	0
Hispanic	253	321
Non-Hispanic	378	445
Unknown Hispanic	0	0
White	432	515
Native Hawaiian	10	9
Black	133	199
Asian	10	4
American Indian	22	12
Multiple Races	24	27
Unknown Race	0	0
Households	471	558
Chronically Homeless	87	77

Unsheltered Statistics

	2018	2019
Individuals	1,685	2,045
Adults (≥25)	1,350	1,718
Youth (18-24)	177	181
Children (≤17)	4	15
Unknown Age	154	131
Male	1,131	1,384
Female	488	548
Transgender	6	11
Gender Non-Con	8	7
Unknown Gender	52	95
Hispanic	492	551
Non-Hispanic	1,009	1,133
Unknown Hispanic	184	361
White	934	1,111
Native Hawaiian	26	21
Black	216	241
Asian	19	26
American Indian	103	66
Multiple Races	52	199
Unknown Race	335	381
Households	1,335	1,843
Chronically Homeless	387	727

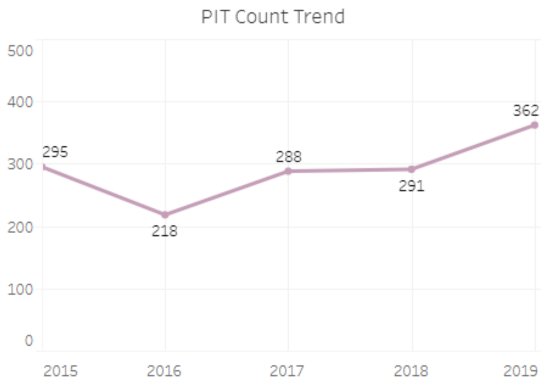
Unsheltered Household Composition
Interview Only

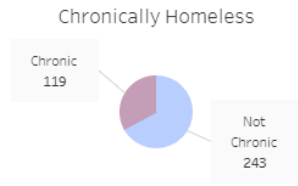
Total Households Interviewed	1,267
Adults Only	1,263
Adults and Children	2
Children Only	2

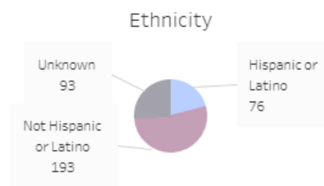
Fig. C2, 2019 Sheltered vs Unsheltered Tableau Dashboard

Unsheltered - Supervisory District 1

2019 Riverside County PIT Count







Subpopulation Statistics

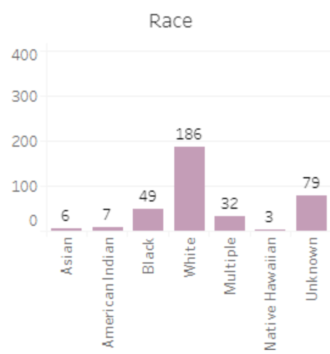
	2018	2019
Total Count	290	362
Interviewed	207	221
Observed	83	141
Adults (≥25)	231	273
Youth (18-24)	39	46
Children (≤17)	0	6
Unknown Age	22	37
Male	192	239
Female	86	88
Transgender	1	6
Gender Non Conforming	1	1
DoesntKnow/NotSure	12	28
Veterans	18	16

PIT Count By City

City	2018	2019
Canyon Lake	0	0
Lake Elsinore	75	66
Riverside*	184	238
Wildomar	15	13
Unincorporated	16	45

Volunteers By Deployment Site

CFLC- Planet Youth	17
City of Riverside Access Center	33
La Sierra University Church	40
Oak Creek Center	3
Operation SafeHouse	61
RSO Lake Elsinore Station	43



Household Composition

Interview Only

Total Households Interviewed	208
Adults Only	206
Adults and Children	1
Children Only	1

Fig. C3, 2019 Supervisory District Tableau Dashboard (Location District 1)

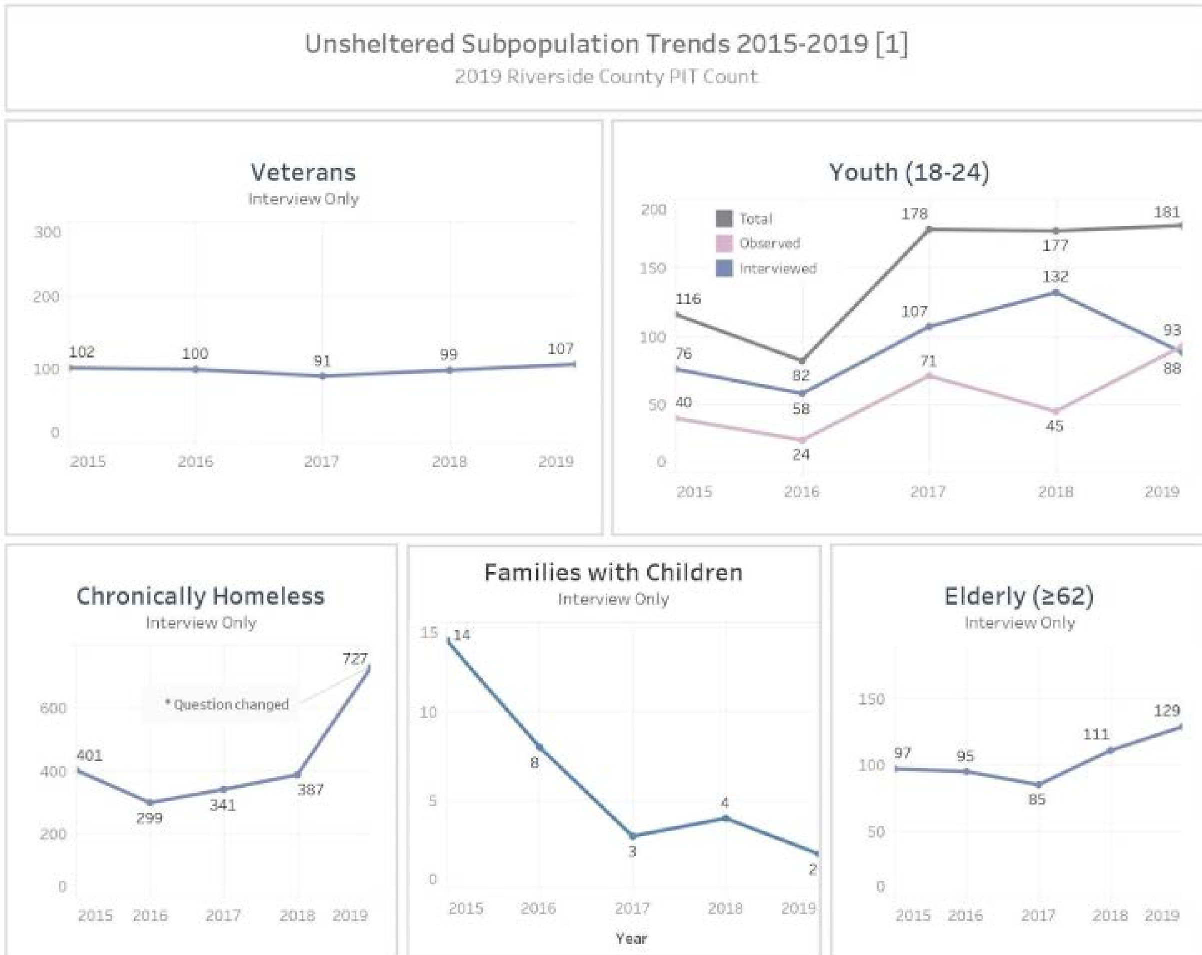


Fig. C4, 2019 Unsheltered Subpopulation Trends Tableau Dashboard 1

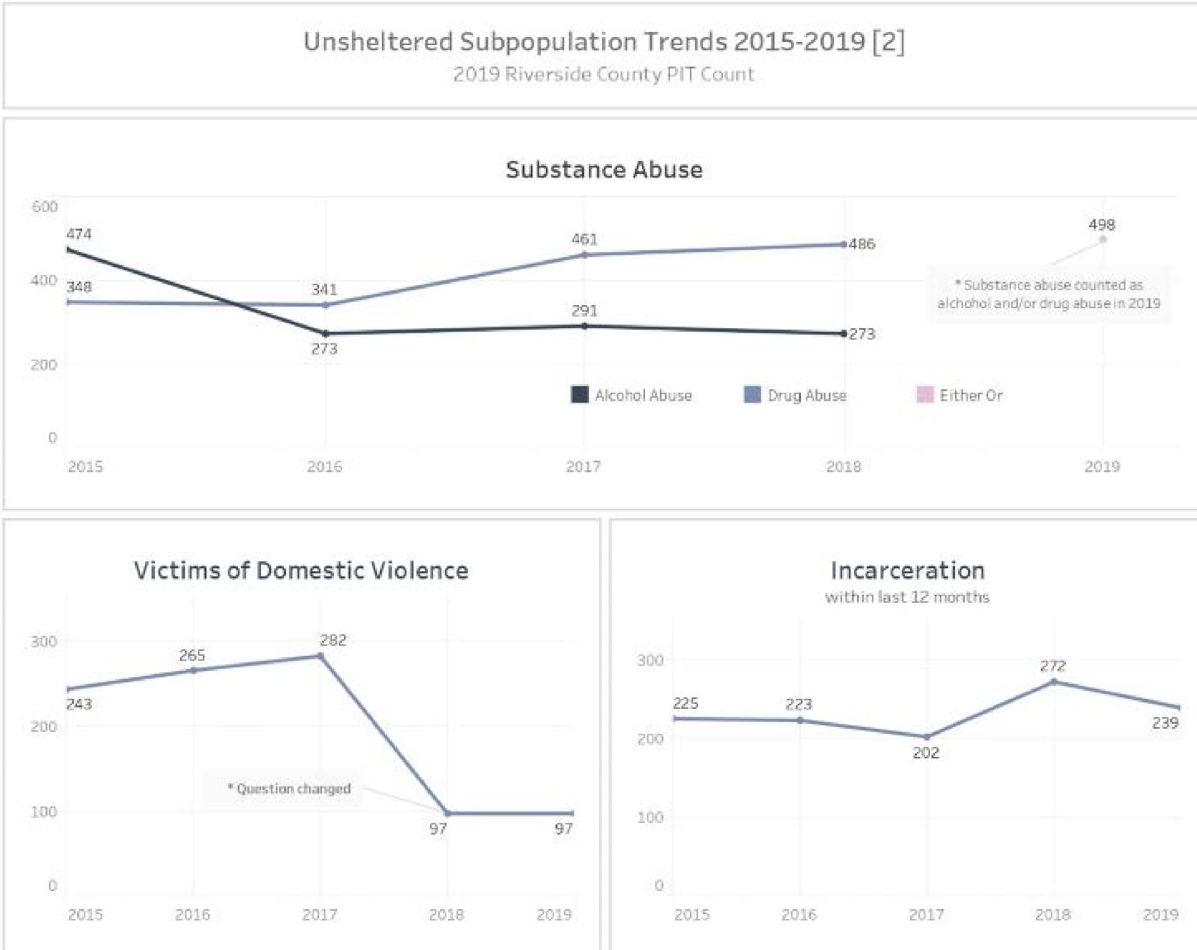


Fig. C5, 2019 Unsheltered Subpopulation Trends Tableau Dashboard 2

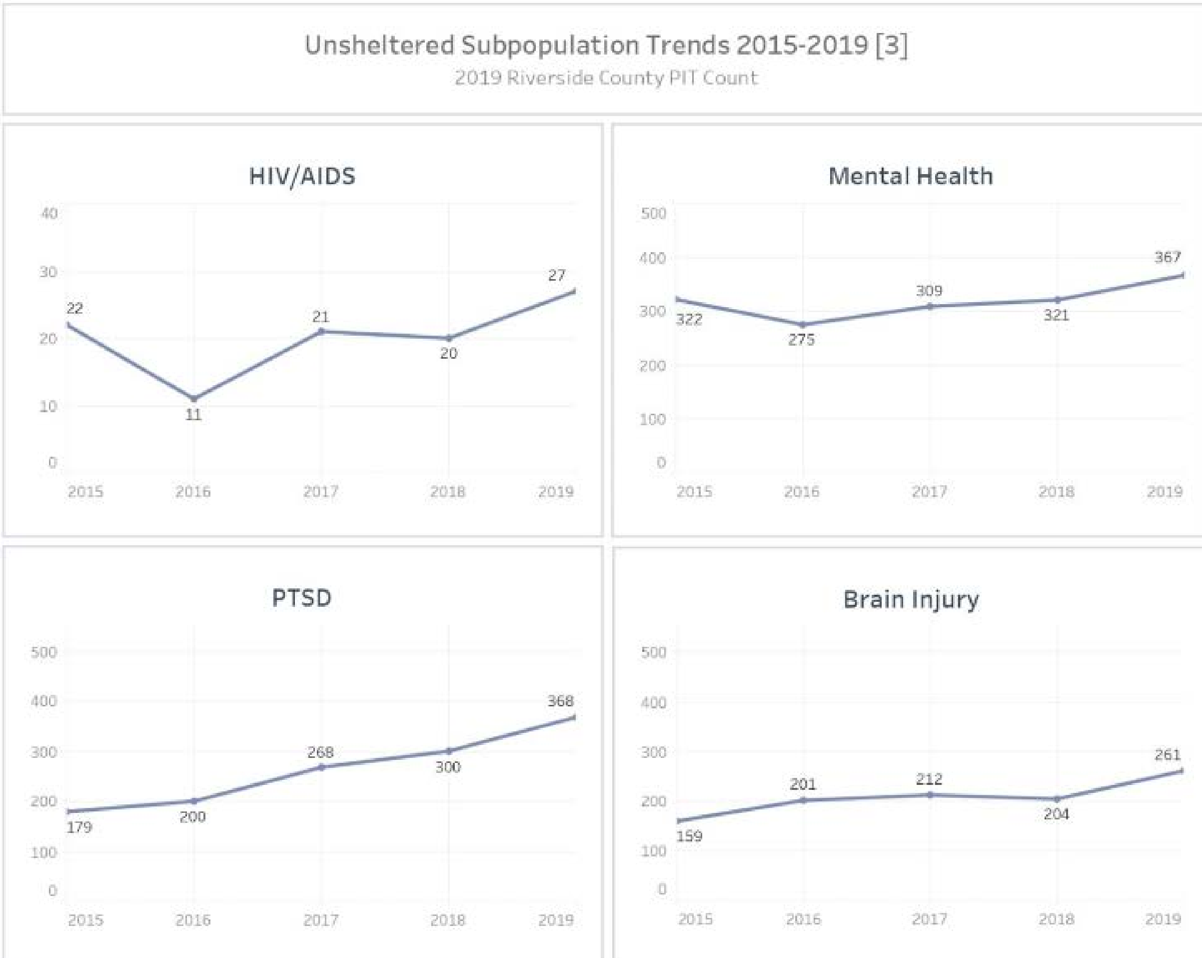


Fig. C6, 2019 Unsheltered Subpopulation Trends Tableau Dashboard 3- Medical History

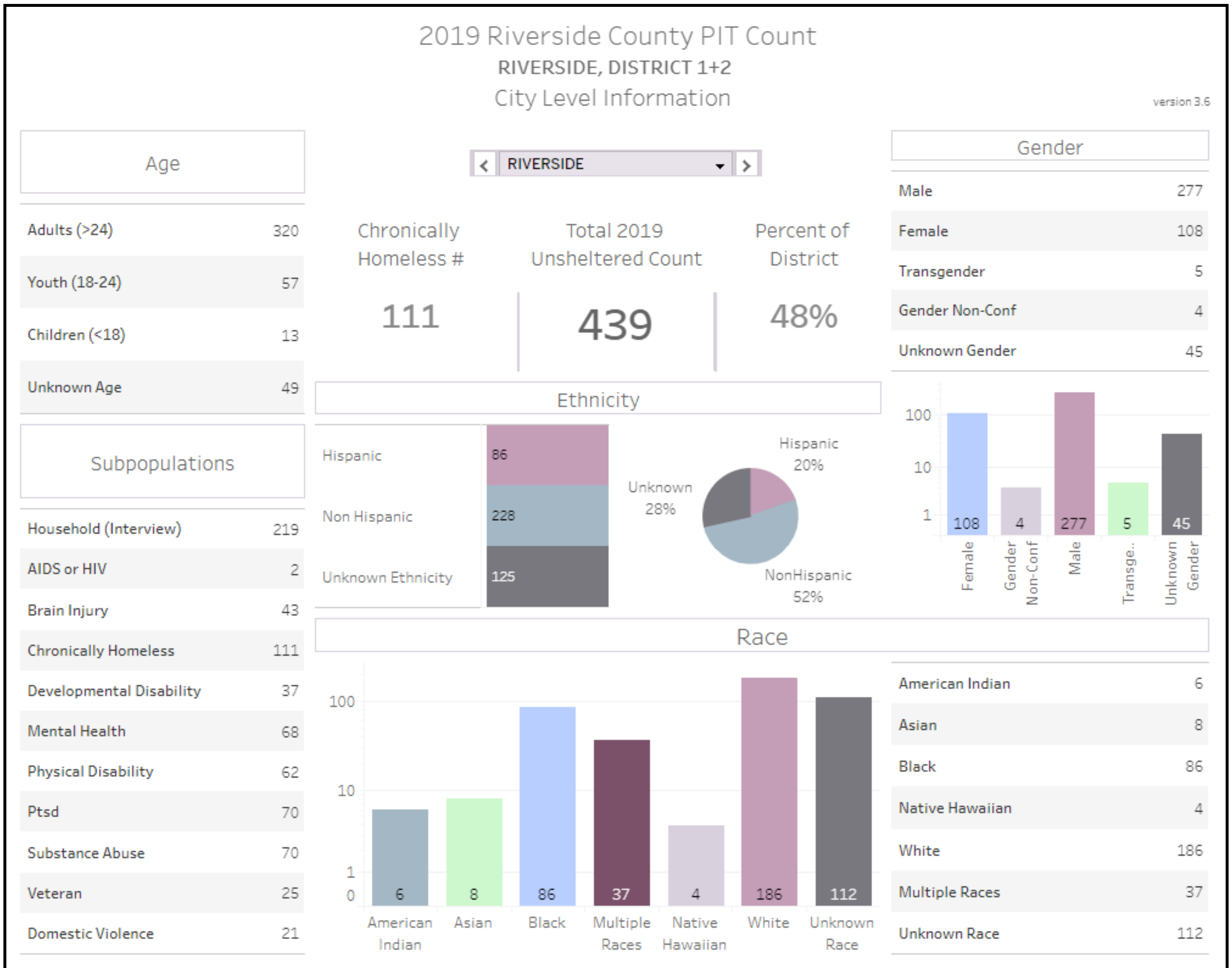


Fig. C7, 2019 City Level Information Tableau Dashboard (Location Riverside Districts 1+2)

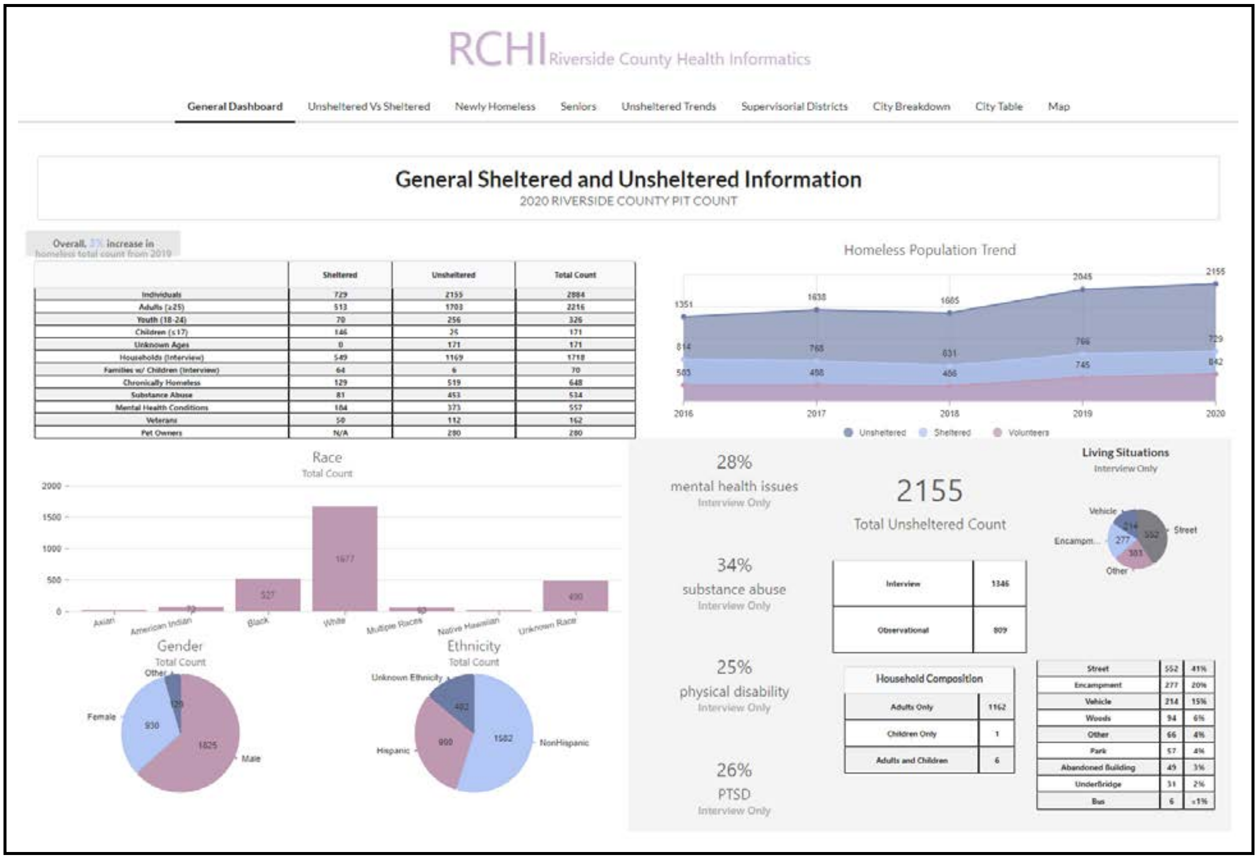


Fig. C8, 2020 General Sheltered and Unsheltered Information Dashboard

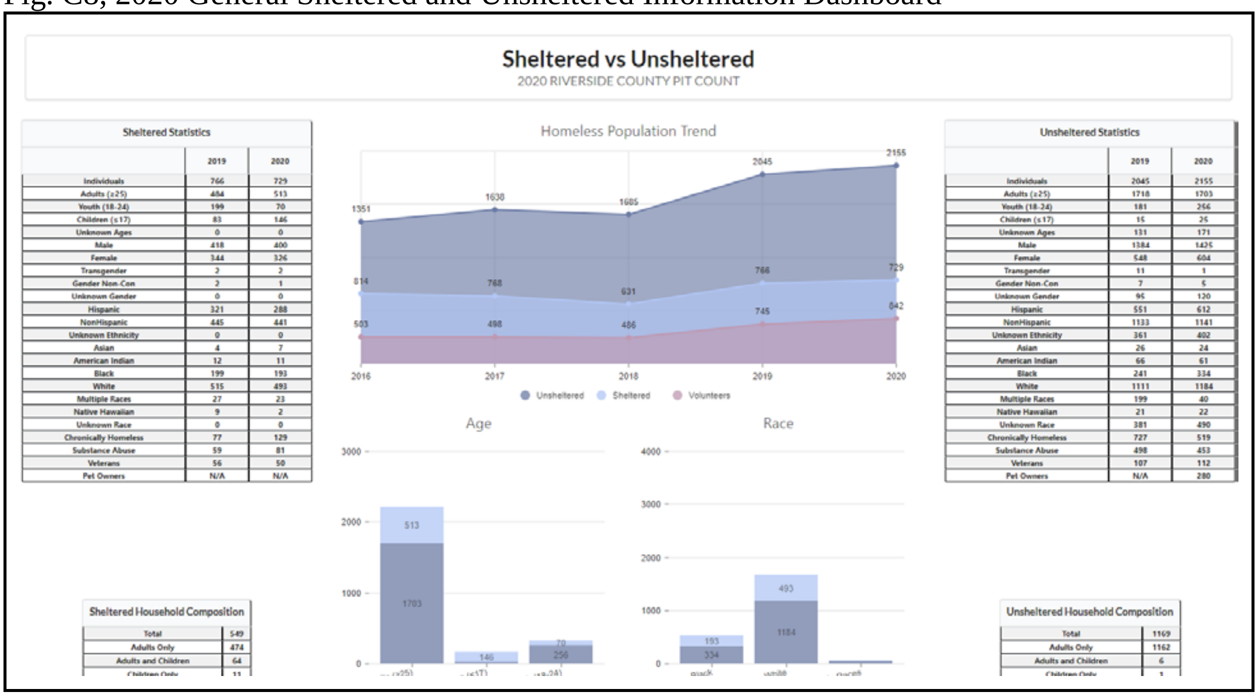


Fig. C9, 2020 Sheltered vs Unsheltered Dashboard

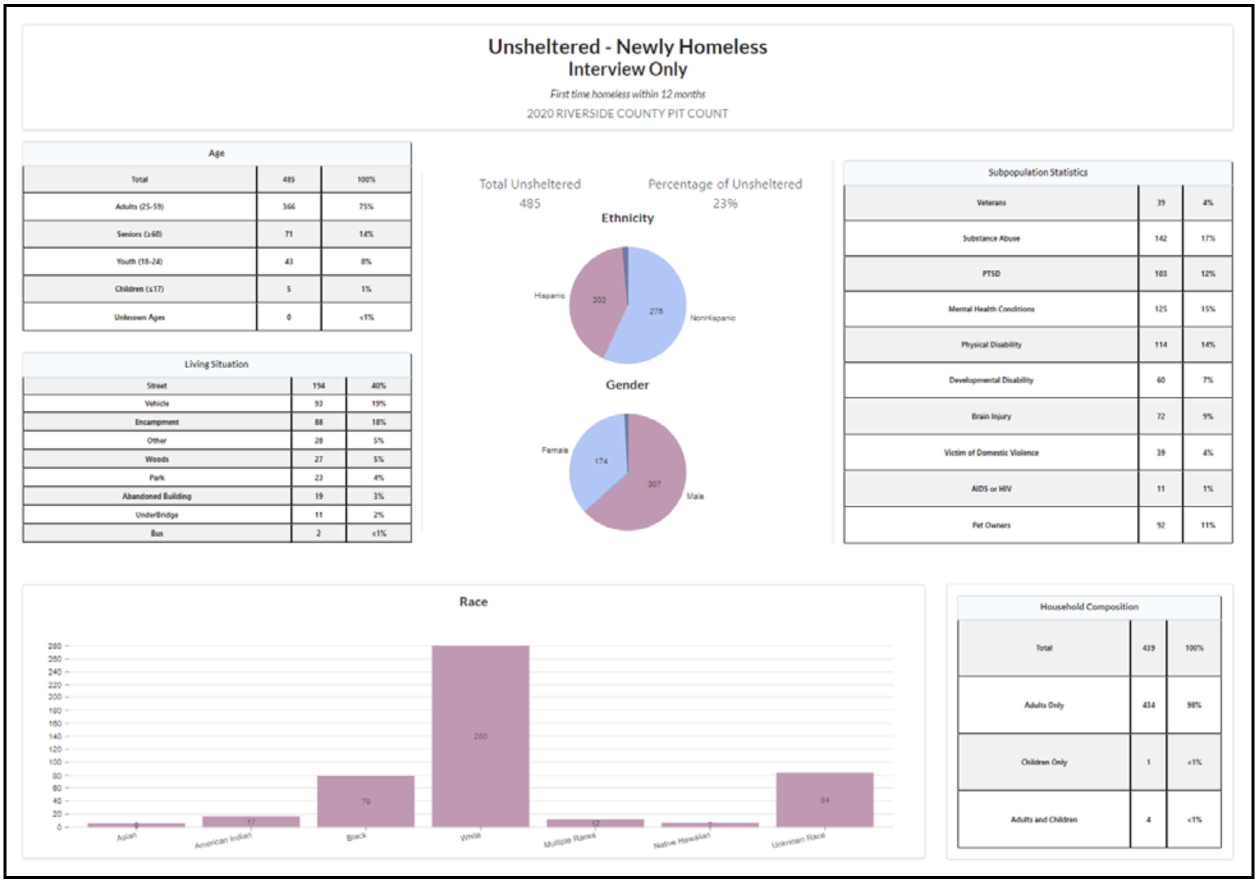


Fig. C10, 2020 Newly Homeless Dashboard

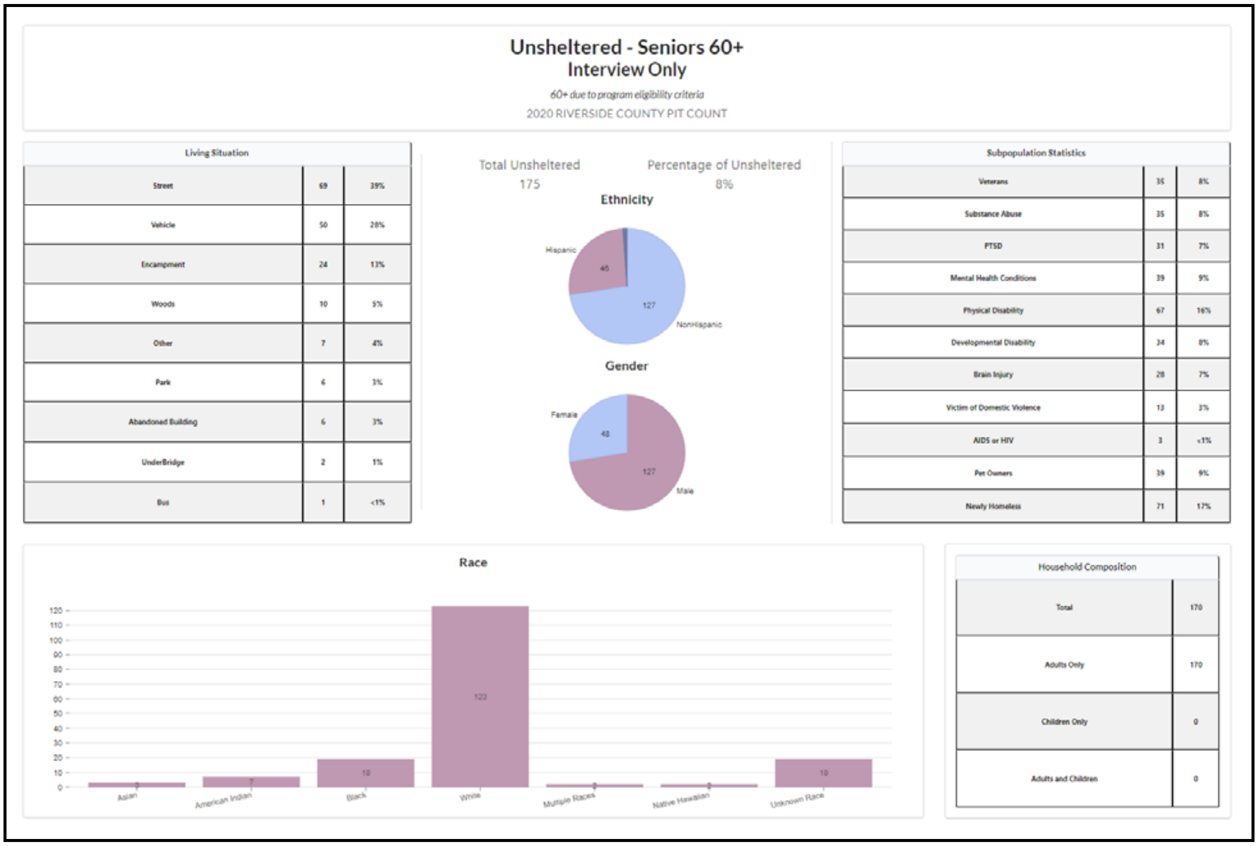


Fig. C11, 2020 Seniors Dashboard

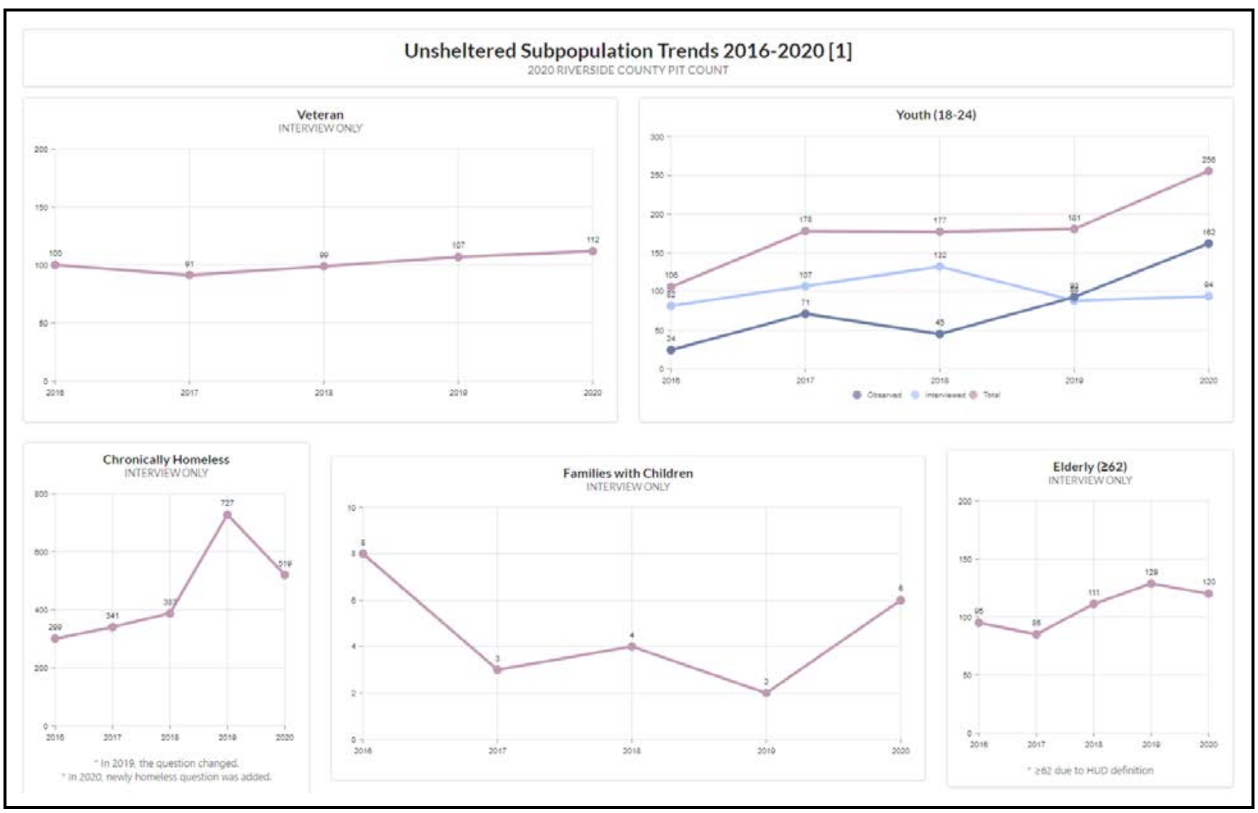


Fig.C12, 2020 Unsheltered Subpopulation Trends Dashboard 1

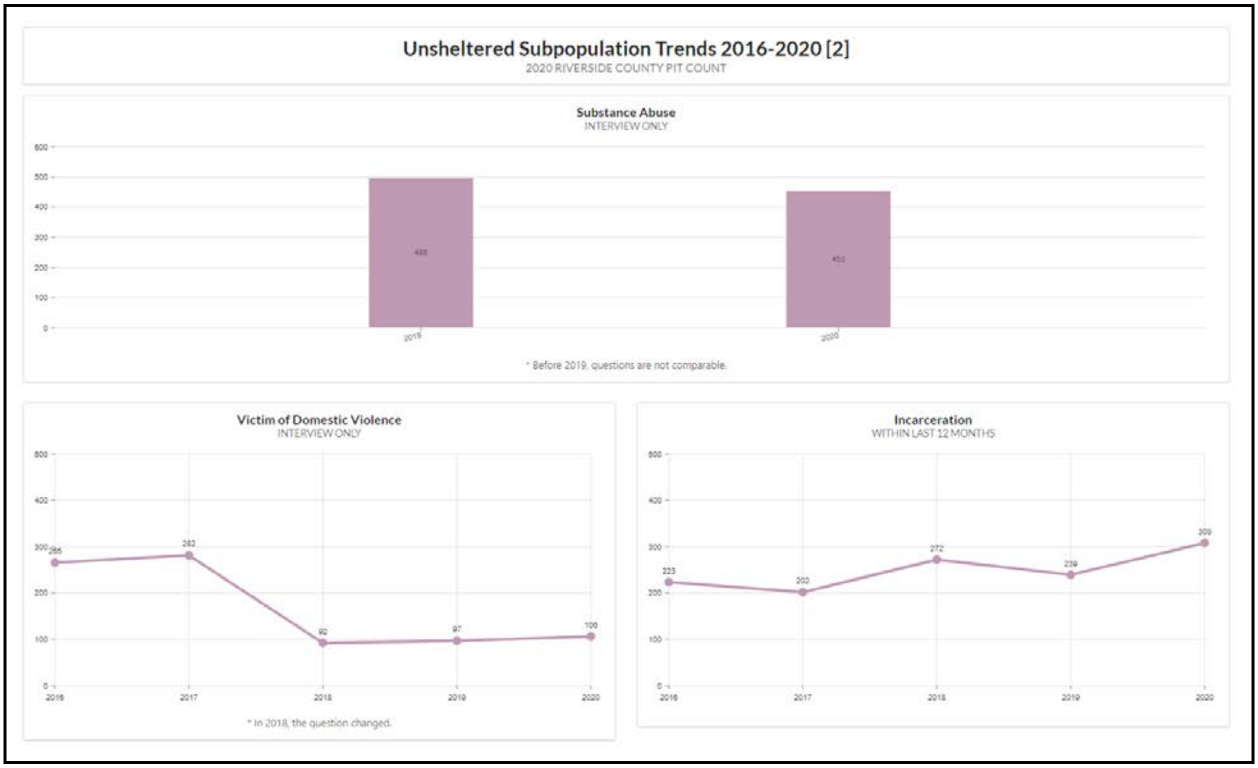


Fig. C13, 2020 Unsheltered Subpopulation Trends Dashboard 2

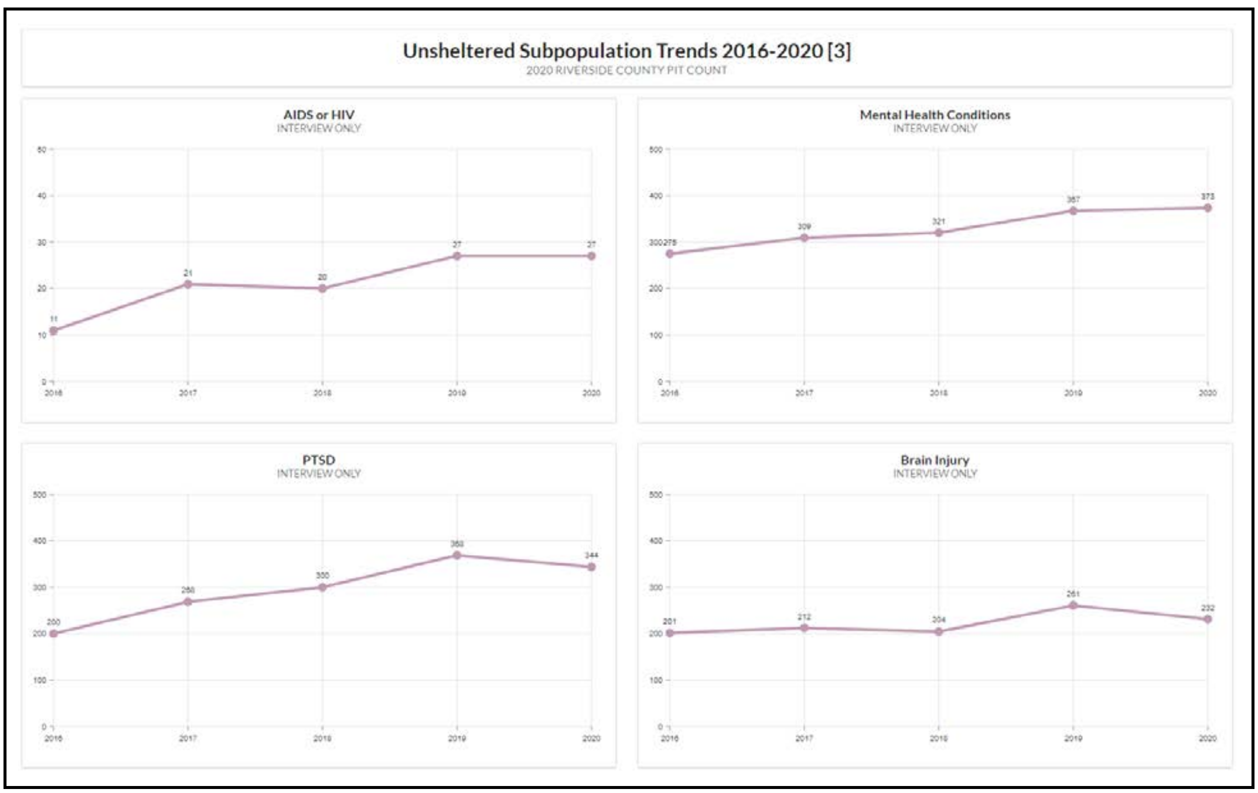


Fig. C14, 2020 Unsheltered Subpopulation Trends Dashboard 3- Mental Health

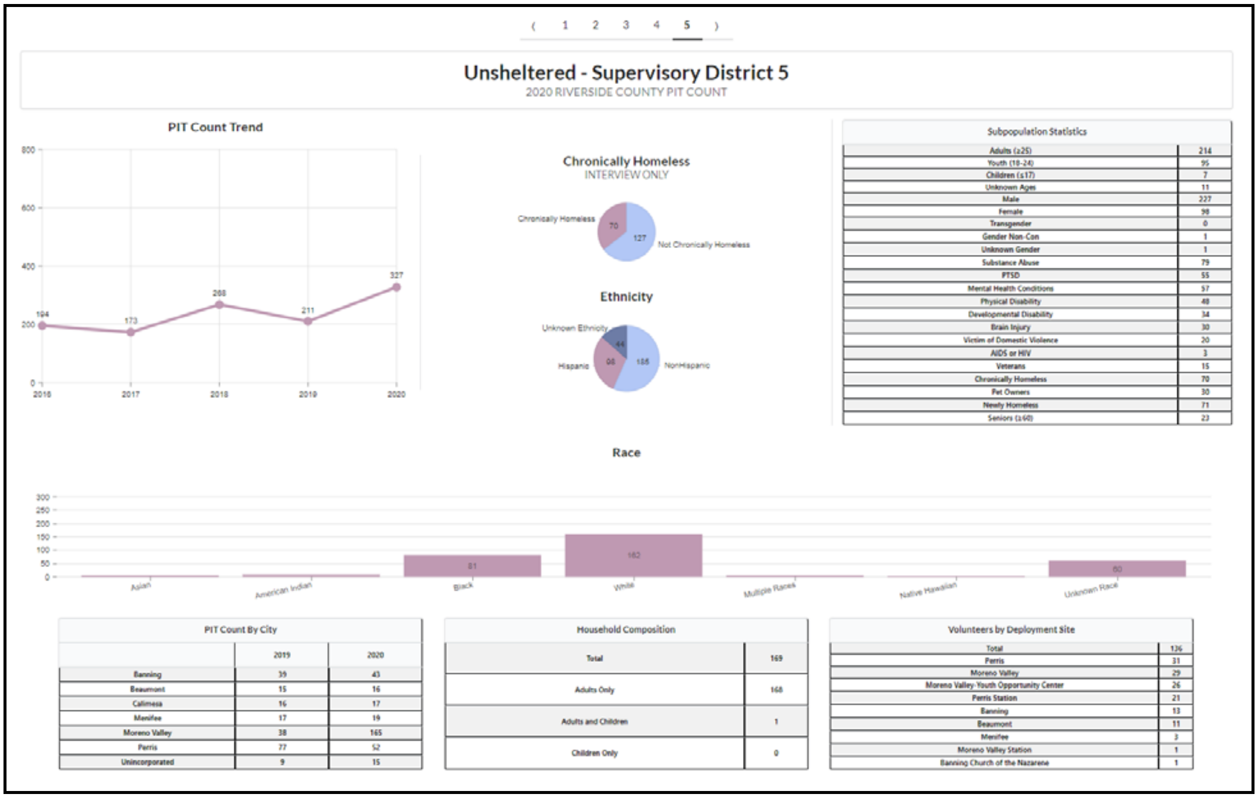


Fig. C15, 2020 Unsheltered Supervisory District Dashboard (Location: District 5)

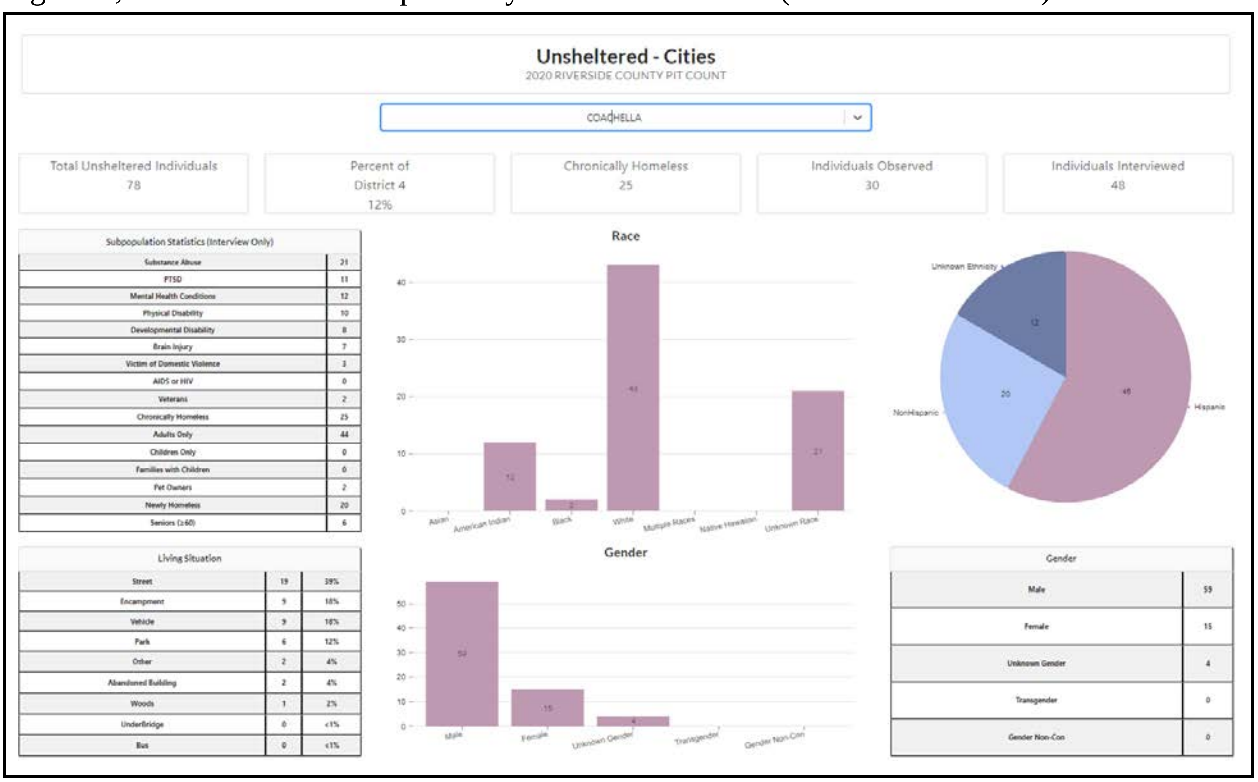


Fig. C16, 2020 Unsheltered City Level Information Dashboard (Location: Coachella)

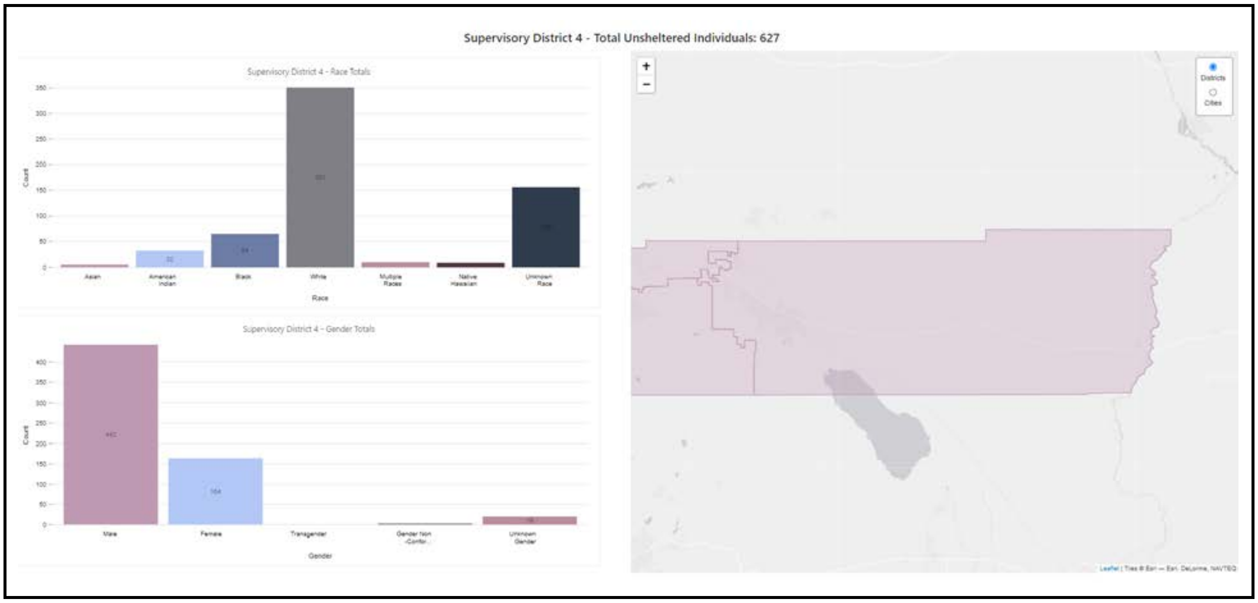


Fig. C17, 2020 Map Dashboard (Location: Supervisory District 4)

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"Notice for Housing Inventory Count (HIC) and Point-in-Time (PIT) Data Collection for Continuum of Care (CoC) Program and the Emergency Solutions Grants (ESG) Program." *HUD.gov*, U.S. Department of Housing and Urban Development, 20 Sept. 2017, www.hud.gov/sites/dfiles/OCHCO/documents/17-08cpdn.pdf.

"Point-in-Time Count Methodology Guide." *HUD.gov*, U.S. Department of Housing and Urban Development, Sept. 2014, files.hudexchange.info/resources/documents/PIT-Count-Methodology-Guide.pdf.